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Hospital Response to Changes in Medicaid Reimbursement

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Abstract

Changes to reimbursement levels and reimbursement methodology have become increasingly common as public health insurance programs seek to slow the rate of cost growth. Despite the fact that Medicaid is a major public health insurance program, little is known about how hospitals respond to price cuts by Medicaid. On the other hand, existing research on hospital response to a commonly used payment method (prospective payment) by Medicaid is largely based on policy changes from the 1980s. In this dissertation, I study 1) how hospitals in California responded to a 10% payment reduction by Medicaid in 2008, and 2) how hospitals in California responded to the 2013 introduction of a prospective payment system by Medicaid. For both analyses, I make use of hospital and emergency department discharge records from the California Office of Statewide Health Planning and Development, and study outcomes related to access to hospital care and intensity of care. I find little response to the 10% payment cut along these margins; suggesting that hospitals may have responded along other margins. In the analysis of hospital response to prospective payment, I find results consistent with theoretical predictions as well as the existing literature. Hospitals responded to prospective payment by reducing average inpatient length of stay. Furthermore, this response was driven primarily by hospitals with the strongest incentives---those previously paid on a per diem basis. These results suggest that hospitals may not respond strongly to across-the-board payment cuts in the way that they treat patients. On the other hand, hospitals had a strong, immediate, and predictable response to a change in the payment methodology, suggesting that perhaps this is a more effective policy tool.

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HOSPITAL RESPONSE TO CHANGES IN MEDICAID REIMBURSEMENT

Dedicated to my parents.

To my dad for inspiring me to get a PhD, and to my mom for never letting me quit.

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Changes to reimbursement levels and reimbursement methodology have become increasingly common as public health insurance programs seek to slow the rate of cost growth. Despite the fact that Medicaid is a major public health insurance program, little is known about how hospitals respond to price cuts by Medicaid. On the other hand, existing research on hospital response to a commonly used payment method (prospective payment) by Medicaid is largely based on policy changes from the 1980s. In this dissertation, I study 1) how hospitals in California responded to a 10% payment reduction by Medicaid in 2008, and 2) how hospitals in California responded to the 2013 introduction of a prospective payment system by Medicaid. For both analyses, I make use of hospital and emergency department discharge records from the California Office of Statewide Health Planning and Development, and study outcomes related to access to hospital care and intensity of care. I find little response to the 10% payment cut along these margins; suggesting that hospitals may have responded along other margins. In the analysis of hospital response to prospective payment, I find results consistent with theoretical predictions as well as the existing literature. Hospitals responded to prospective payment by reducing average inpatient length of stay. Furthermore, this response was driven primarily by hospitals with the strongest incentives—those previously paid on a per diem basis. These results suggest that hospitals may not respond strongly to across-the-board payment cuts in the

way that they treat patients. On the other hand, hospitals had a strong, immediate, and predictable response to a change in the payment methodology, suggesting that perhaps this is a more effective policy tool.

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CHAPTER 1 : Introduction

Health insurance plans have long used supply-side financial incentives in efforts to slow health care cost growth. Changes in the level and structure of reimbursement are often used to align the incentives of providers and insurers, particularly within public insurance programs such as Medicaid.

In this dissertation, I examine two recent major changes to Medicaid payment rates in the state of California. The first was a payment decrease in 2008 that affected about a third of the hospitals in the state. The fee cut amounted to at least a ten percent decrease of rates from the previous level, and was a substantial decrease that affected acute care services provided to Medicaid fee-for-service patients by certain general acute care hospitals. The second was a change in the reimbursement methodology that took place in 2013. Prior to this change, hospitals were reimbursed for fee-for-service Medicaid patients either on a per diem basis (i.e. they were paid a fix rate per day of inpatient stay), or on a fee-for-service basis, depending on hospital type. After July 2013, the state switched to a diagnosis-related group (DRG) reimbursement scheme for all general acute care hospitals, whereby hospitals were reimbursed per inpatient *stay*, rather than inpatient day or on a cost basis. *This thesis tests the hypothesis that hospitals respond to reductions in payment by reducing the amount of care provided to Medicaid patients, increasing the amount of care provided to higher-paying, non-Medicaid patients, or both. This thesis also tests the hypothesis that hospitals reimbursed on a fee-for-service basis will respond to the introduction of DRG payments by decreasing both the length of stay and the amount of treatment provided, but that hospitals previously paid on a per diem basis will reduce only length of stay under DRG payments.*

Much of the existing literature regarding provider response to payment changes or payment differentials focuses on the Medicare program or on the treatment of Medicaid patients compared to patients with other insurance. Lindrooth et al. (2007) find that following a reduction in Medicare reimbursement rates, hospitals with a higher share of Medicare patients lowered treatment intensity for generously reimbursed services. Studying the impact of physician fees on treatment intensity in the context of Cesarean versus normal childbirth, Gruber et al. (1999) find that due to Medicaid's relatively low reimbursement differential between the two procedures, a reduction in reimbursement rates would result in reduced treatment intensity for Medicaid patients. In the literature specifically surrounding hospital response to payment reductions, the most commonly studied outcome is cost shifting – the notion that in response to a decrease in payments from a public payer, hospitals will increase prices to private payers. Dranove (1988) notes that even theoretically, strict conditions need to hold for cost-shifting to occur. Broad reviews of the literature show that empirically, the occurrence of cost shifting is at most very rare and limited (Morrisey, 1996; Frakt, 2011) and some work has shown that private payments may even fall in response to payment reductions by Medicare (White, 2013). Thus, cost-shifting appears to play a minimal role at most, and there is no consensus in the literature about hospitals' response to fee cuts. A number of other responses to payment changes are possible; Ellis (1998) notes that providers may overprovide care to low-cost patients, underprovide care to high-cost patients, or avoid high-cost patients. Dafny (2005) examines a change in relative reimbursements by Medicare, and finds that the majority of the response was administrative (i.e. changes in billing) as opposed to real changes in patient care. However, hospital response to broad price cuts is not yet well understood and research on other potential responses to payment cuts is limited. This is especially true of cuts made by Medicaid, which generally has the lowest reimbursement rates among any payer. While a large literature exists on hospital response to prospective payment systems, the majority of it focuses on state or federal policy changes from the 1980s (Rosko and Broyles, 1987; Ellis and McGuire, 1996). These articles do find substantial responses to prospective payments—significant reduction of cost growth is found in states where prospective payment in instituted, with cost savings coming about mainly from reduced length of stay. Over the past 30 years, health care costs have risen tremendously, there has been a large shift into managed care insurance plans, and there have been a number of major changes in healthcare policy, including the Affordable Care Act. Given the rapidly changing healthcare landscape in the United States, it is important to understand how incentives brought about by prospective payment may impact hospital behavior today.

This dissertation contributes to the literature in several ways. First, there is a general paucity of research in the health economics literature regarding state Medicaid programs (as they generally pose a challenge in terms of institutional knowledge). Second, as previously mentioned, research on hospital response to payment changes has largely centered around relative changes in rates within the Medicare program. The current research will explore the effects of broader fee cuts by Medicaid that impact all general acute care inpatient services. Finally, this project will examine hospital response to a re-structuring of the payment methodology to a DRG-based system. A number of studies have examined the introduction of the Medicare DRG system, but its introduction in 1982 does not lead to obvious conclusions as to how hospitals may respond today in a vastly different health care landscape. Furthermore, analysis of other states' experience with implementing DRG programs is largely outdated. This work also represents a major contribution to the literature in that it is able to separately identify hospital response to a DRG system based on previous method of reimbursement.

The motivation behind this work is to shed light on the ways hospitals may respond to changes in reimbursement by Medicaid. It has become increasingly common for states to respond to fiscal pressure by cutting provider rates, and yet it is not well understood how this might affect treatment and access to care. Policymakers often argue that there are inefficiencies in the health care system, and cutting reimbursement rates will simply encourage providers to reduce the inefficiencies in their systems. However, it is not obvious that this is the case. Hospitals are likely to continue seeing payment reductions by state Medicaid programs in the coming years if current trends continue. It may be the case that taxpayers and policymakers are willing to trade off changes to care and access to care for Medicaid patients in exchange for a reduction in the growth rate of Medicaid spending. However, it is not possible to know this without quantifying the impacts of changes to reimbursement on patient care. It is therefore very important to have a more complete understanding of how hospitals respond to broad cuts to payments by Medicaid. As described above, some work has explored hospital response to payment decreases by Medicare, but it is not immediately clear that hospitals would have a similar response to decreases by Medicaid. Furthermore, for other states considering policy changes seeking to provide hospitals with incentives to decrease costs, results from California's recent experience with the shift to a DRG system will be very relevant.

1.1. Prior Literature

The literature regarding hospital response to payment changes has largely focused on one particular hypothesis: cost shifting. Cost shifting is the notion that in response to a decrease in payments from a public payer, hospitals will increase prices to private payers to make up the losses. Despite a large body of literature, there has been little reliable evidence in support of cost shifting, suggesting that this response is at most rare and limited (Morrisey, 1996; Frakt, 2011). However, cost shifting is only one of a number of ways hospitals may respond to a change in payment from a public payer, and the lack of evidence for the cost shifting hypothesis leads to the conclusion that hospitals must largely respond in other ways. A smaller literature has examined the other varied responses that a hospital may have in response to a payment decrease. For example, hospitals may alter the way they treat patients affected by the payment changes (Ellis, 1998), change the way they treat other patients (Ellis, 1998; David et al., 2014), or make administrative changes to elicit higher payments without altering actual treatment (Dafny, 2005). A number of papers have looked at hospital response to the introduction of prospective payment systems, but generally draw on decades-past policy changes. I review the literature in greater detail below.

1.1.1. Hospital Response to Payment Cuts

Cost-Shifting Papers

A large body of literature has examined both the theoretical and empirical existence of cost shifting. Dranove (1988) wrote the seminal model of hospital response to payment changes, showing the theoretical conditions that need to hold for cost shifting to occur. Building off the earlier work on non-profit hospitals by Newhouse (1970) and Pauly and Redisch (1973), Dranove presents a model of hospital utility that maximizes both profits and quantity in two separate markets. The hospital then sets prices to maximize the objective function:

$$U = U\left(\pi^i\left(P^i, C^i\right) + \pi^j\left(P^j, C^j\right), Q^i\left(P^i\right), Q^j\left(P^j\right)\right) \tag{1.1}$$

where i and j denote the two markets, and P and C denote prices and costs, respectively. Dranove shows that even theoretically, cost shifting only occurs when certain conditions have been met; first, the hospital cannot be a pure profit maximizer, and second, the hospital must have market power.

Empirical studies have also found limited evidence of cost shifting. Hadley et al. (1996) note that cost shifting behavior could occur not only in response to a reduction in prices by some payers, but also from other financial stresses such as increases in uncompensated care or increases in competition. However, the authors find that in response to low profits and high competition, hospitals may increase efficiency or reduce costs, but that there is no evidence to support the cost shifting hypothesis. Morrisey (1996) provides a review of the empirical evidence on cost shifting. Cross sectional studies generally found no evidence of cost shifting, but many suffered from an inability to control for the level of service, quality, and amenities. However, dynamic studies that were able to control for these factors also found no evidence of cost shifting. Morrisey suggests that the theoretical conditions which must hold for cost shifting to occur were unlikely to exist, and hospitals were likely to respond to falling prices by reducing the amount of uncompensated care they provide.

Cutler (1998) finds some of the only credible evidence of cost shifting, but still shows that its extent is limited. Studying reductions to Medicare payments in the late 1980s and the early 1990s, Cutler finds that while cost shifting did seem to be the primary response in the 1980s, by the 1990s, cost shifting was no longer a viable response for hospitals. Instead, hospitals turned to other cost-cutting measures such as reduction of nursing staff and reduction of capacity. Cutler also examined other potential responses, such as reductions in the acquisition of new technologies and removal of services that primarily serve the poor, and found little evidence supporting these hypotheses.

Others have also pointed out that cost shifting need not be the only way a hospital might respond to reductions in payment. Frakt (2011) notes that cost shifting is only one of a number of potential hospital responses to decreases in public payment rates, specifically noting that cost *cutting* may also be likely to occur. Frakt updates Morrisey's 1996 review, providing a comprehensive review of the more recent empirical literature. He includes cross-sectional studies, fixed-effects specifications, and difference models. He finds that much of the literature that finds substantial cost-shifting is based on descriptive, industry-wide hospital payment-to-cost margins, which does not allow for careful analysis of cost shifting as opposed to simple price discrimination. Studies that are more careful in their analysis find that cost shifting may occur, but relatively infrequently. Furthermore, Cutler (1998) is the only paper to find evidence of full dollar-for-dollar cost shifting.

More recent evidence has even found the opposite of cost shifting to occur—the lowering of private prices in response to a decrease in rates from public payers. White (2013) examines hospital spending in areas with relatively low Medicare spending, and finds that these areas actually experienced relatively low growth in private payment rates. Regression analyses show that a 10% cut in Medicare rates actually resulted in a 3-8% cut in private payment rates. The author hypothesizes that this may be a result of spillover effects of efficiency measures hospitals may undertake to cut costs, or part of strategic efforts to attract more privately insured patients.

Although cost shifting remains a popular topic among economists, policymakers, and hospitals, the empirical literature seems to show that its true extent is fairly limited. Based on this previous research, I focus my empirical analyses on other potential responses of hospitals to payment reductions.

Other Responses to Fee Changes

A smaller literature has examined other potential effects of fee changes on hospital behavior. Ellis (1998) notes that as reimbursement incentives are increasingly used to influence provider behavior, it is important to understand how these forces affect patient treatment. Ellis focuses on three potential provider responses to reimbursement incentives: 1) creaming, the overprovision of services to low-cost patients, 2) skimping, the underprovision of services to high-cost patients, and 3) dumping, the avoidance of high-cost patients. Ellis determines that theoretically, a fee-for-service or cost-based reimbursement system will result in overprovision of services to all patient types. He also finds that when providers dump high severity patients, they also engage in skimping behavior. Empirical evidence supporting this theoretical work is provided in White and Yee (2013). In this paper, the authors study hospital response to Medicare price cuts between 1995 and 2009, and find that a 10% reduction in Medicare prices leads to a 4.6% reduction in hospital discharges among the elderly, i.e., a "dumping" response.

Dafny (2005) examines hospital response to a change in payment rates by Medicare. The author takes advantage of a 1988 policy change that resulted in large price changes for 40% of diagnosis-related groups (DRGs). Using this policy change as an exogenous source of variation, Dafny finds that the primary response among hospitals was so-called "upcoding", or the practice of coding patients to diagnoses with higher DRG weights to receive higher reimbursement. Contrary to previous literature, she finds little evidence of real response to fee changes in the form of intensity or quality of care. This suggests that hospitals are responsive to targeted changes to the fee schedule, but may try to avoid changes to patient care.

Finally, there is some evidence that in response to financial pressures, hospitals may cease to offer some unprofitable services or services primarily used by higher-cost, lower-paying patients. Dranove et al. (2013) examine hospital response to negative financial shocks by studying the differential impact of the 2008 financial recession on hospital endowments. The authors propose a number of potential hospital responses (in addition to cost shifting): changes in hospital staffing, offering of low-profit services (such as trauma centers of psychiatric services), and level of investment in new technologies, specifically electronic medical record systems. The authors do not find substantial evidence of cost shifting, but do find that hospitals with large negative shocks to their endowments delayed purchases of health information technology and reduced their offerings of unprofitable services.

Another avenue through which changes to Medicaid reimbursements may impact hospital behavior is through the potential for cross-subsidization. Cross subsidization in the hospital setting refers to hospitals subsidizing unprofitable care for the Medicaid or uninsured population by charger higher prices to the privately insured population (or, subsidizing the provision of unprofitable services with the provision of profitable ones). Previous work has provided evidence that cross subsidization does in fact occur broadly in hospitals to allow for the provision of unprofitable services(David et al., 2014). However, some research has noted that due to increasing competition in the hospital industry, as well as increasing price transparency, the next decade could bring an increasing need for hospital cross-subsidization, but a declining ability to do so (Altman et al., 2006). Therefore, it is possible that the changes to Medicaid reimbursement could affect treatment not only for Medicaid patients, but for other patients as well.

Limited evidence exists regarding potential responses of hospitals to fee decreases by

Medicaid. This dissertation seeks to address this gap in the literature.

1.1.2. Hospital Response to DRG Implementation

A number of papers have studied the impact of prospective payment on hospital behavior. Rosko and Broyles (1987) examine the short term response of hospitals to a DRG pricing system by Medicaid. The authors examine the response of hospitals to the implementation of a DRG system in the early 1980s by the New Jersey Department of Health, using hospitals in eastern Pennsylvania that were reimbursed retrospectively as a control group. Regression analyses showed that a cost savings of 14.1 percent per admission and 9.8 percent per day occurred in hospitals subject to prospective payment. Furthermore, although not statistically significant, length of stay fell by an average of 6.5 percent. These findings are consistent with the idea that a shift to a prospective payment system will motivate hospitals to increase the profitability of each inpatient stay, primarily by decreasing length of stay.

Frank and Lave (1989) estimate a model of hospital length of stay for Medicaid psychiatric patients, comparing per case prospective payment with cost-based reimbursement. Using a comparison of hospital discharges in states with different Medicaid payment models, the authors find that compared with cost-based reimbursement, there is a significant reduction in length of hospital stay associated with prospective payment. Somewhat more recently, Ellis and McGuire (1996) investigated hospital response to the 1989 shift to a DRG system by New Hampshire Medicaid. Specifically, they evaluate three potential responses of hospitals to a change in reimbursement incentives: changing intensity of services, changing the patient type or patient severity seen at the hospital, or changing the market share. Using both Medicaid data and New Hampshire hospital discharge data, the authors find that compared to a non-Medicaid population, Medicaid patients experienced a 14.5% reduction in length of stay as a result of the prospective payment system. A number of other papers also find similar responses to DRG-based payments (Gay et al., 1989; Freiman et al., 1989; Scheffler et al., 1994; Eldenburg and Kallapur, 1997).

While a large body of research exists that addresses hospital response to a switch to a DRG system, much of it uses policy changes from over thirty years ago, when the healthcare landscape in the U.S. was very different. This dissertation updates this older strain of research, and also conducts a comparison of response to DRG implementation based on prior reimbursement method (per diem versus FFS).

1.2. Policy Background

The Medicaid program was created (along with Medicare) as a provision of the Social Security Amendments of 1965 to provide health insurance coverage for individuals and families with low income. Medicaid is a means-tested program jointly funded by the state and federal governments, but managed by each state. States also have broad decision-making power in terms of eligibility, benefits, and reimbursement associated with the program.

The California Medical Assistance program, or Medi-Cal, is California's state Medicaid program, and is jointly administered and financed by the California Department of Health Care Services (DHCS) and the Centers for Medicare and Medicaid Services (CMS). The goal of Medi-Cal is to provide health insurance coverage to low-income individuals, particularly families with children, seniors, the disabled, those in foster care, pregnant women, and low-income individuals with certain conditions such as tuberculosis, breast cancer, or HIV/AIDS(DHCS, 2014a).

1.2.1. Hospital Payment Scheme

In the early 1980s, a combination of a large state budget deficit and substantial excess capacity of hospital inpatient beds in California led legislators to seek reform to the existing fee-for-service based payment system (DHCS, 2014d). Prior to 1982, hospitals were reimbursed by Medi-Cal under a cost-based reimbursement system. The Selective Provider Contracting Program (SPCP) was established in 1982 in an effort to allow DHCS to control Medi-Cal costs without restricting hospital access for beneficiaries. The SPCP allowed DHCS to contract on a competitive basis with hospitals willing to provide inpatient care to Medi-Cal beneficiaries at a negotiated daily capitated rate, or per diem rate, for all services. This model was intended to give hospitals an incentive to improve efficiency of care and control costs. The concept was that Medi-Cal beneficiaries would receive care at only those hospitals that contracted with DHCS.

However, the legislation also required that sufficient hospital beds and services remain available to all Medi-Cal beneficiaries. Accordingly, geographic areas of the state known as Health Facility Planning Areas (HFPAs) were designated as "closed" areas or "open" areas based on the level of hospital competition in the area. Closed HFPAs were more competitive areas, where SPCP contracts had been signed with some hospitals, and Medi-Cal beneficiaries were required to receive inpatient care at a contract hospital (other than in emergencies or other specific circumstances described by the Welfare and Institutions code section 14087[1]). In open HFPAs, the SPCP was not in effect, primarily because these were more rural areas with few hospitals, and the amount of competition in the market was not sufficient to induce hospitals to

[1] Additional exclusions include services provided to Medi-Cal beneficiaries dually eligible for Medicare, services provided to Medi-Cal Managed Care patients, and services provided to patients living a certain distance from a contract hospital.

contract. As such, to ensure sufficient access to care for Medi-Cal beneficiaries in these areas, beneficiaries were allowed to receive inpatient care at any hospital in the open HFPA. While hospitals could still choose to contract with DHCS, there was no penalty for not doing so. Non-contract hospitals in open HFPAs were initially reimbursed an interim charge-based rate that was negotiated with Medi-Cal. This rate was negotiated as a set percentage of the hospital's charges. The reimbursement was later adjusted based on Medi-Cal allowable audited costs (DHCS, 2014b).[2] Table 1 summarizes the payment system.

1.2.2. 2008 Fee Decrease to Non-Contract Hospitals

Due to state fiscal constraints, an effort was made to rein in costs associated with Medi-Cal in 2008. Effective July 1, 2008, DHCS was required to reduce the interim payment made for inpatient services for many non-contract hospitals. Specifically, DHCS was required to limit the interim payment to the *lesser* of the interim rate less 10%, or the applicable regional average per diem contract rate for tertiary and non-tertiary hospitals, less 5%. Furthermore, when calculating the cost report settlement for a non-contract hospital for inpatient services, DHCS was required to limit the settlement to the *lesser* of the hospital's audited allowable cost less 10%, or the applicable regional average per diem contract rate for tertiary and non-tertiary hospitals less 5%. These reductions applied to non-contract hospitals only. Specifically, they applied to(DHCS, 2008):

1. All non-contract hospitals in closed HFPAs

2. Non-contract hospitals in open HFPAs that were closed at any point on or after July 1, 2005, but were open on July 1, 2008

[2] Note that this payment scheme applies only to Medi-Cal fee-for-service patients, and does not apply to Medi-Cal managed care.

3. Non-contract hospitals in open HFPAs on July 1, 2008, regardless of whether the area had ever been closed, if there were three or more hospitals with licensed general acute care beds in the HFPA

Exemptions also existed for certain types of hospitals, including:

1. Small and rural hospitals

2. Non-contract hospitals in open HFPAs on July 1, 2008, if there were fewer than three hospitals with licensed general acute care beds in the HFPA

Essentially, this entailed a decrease in fees of at least 10% to all affected hospitals for inpatient services. Of the 388 general care hospitals in California between 2007 and 2009, 94 hospitals were subject to this cut (Figure 2).[3]

1.2.3. 2013 Switch to DRG System

In 2010, the Statutes of 2010 mandated the design and implementation of a new reimbursement methodology for hospital inpatient services provided to fee-for-service Medi-Cal beneficiaries (DHCS, 2014b). This system was to be based on diagnosis related groups (DRGs), a system that the federal Medicare program had been using since 1983. Generally, DRGs provide a classification scheme for inpatient admissions. Each DRG is a definition of case types meant to represent patients who would be expected to receive similar services and incur, on average, similar costs during the hospital stay (Fetter et al., 1980). Then, each inpatient admission is assigned a DRG,

[3]Given that non-contract hospitals were initially reimbursed as a percentage of their charges, there could be concern that hospitals may simply have increased charges in response to the fee decrease. However, this is unlikely for two reasons. First, hospitals were only permitted to charge Medi-Cal a certain percentage of the average charges they applied to other payers. Second, the fee decrease was the *lesser* of a ten percent reduction to charges or a five percent reduction of the average regional per diem contract rate, so hospitals would have seen a reduction to payments regardless of any strategic changes to their charges.

and hospitals are paid a capitated amount for that DRG, regardless of what services were actually provided and how long the patient remained in the hospital. There are a number of methodologies for classifying DRGs, including the original system Medicare used, the Centers for Medicare and Medicaid Services (CMS)-DRG, the system Medicare currently uses, Medicare Severity (MS)-DRGs, and the system that is currently in use by Medi-Cal, All Patient Refined (APR)-DRGs.

Similar to other DRGs systems, the APR-DRG system works by assigning a DRG to each stay, taking into account not only the patient's diagnoses, but also age, procedures performed, and discharge status. Then, each stay is assigned a severity level on a four point scale (minor, moderate, major, extreme). The DRG-severity combination is assigned a DRG weight that allows it to be compared to the resource use and cost of the "average patient." A base DRG price is determined by DHCS, and the amount paid to the hospital is then the DRG base price multiplied by the DRG weight. The APR-DRG system is used by Medi-Cal (and a number of other state Medicaid programs) rather than the CMS-DRG or MS-DRG systems because the Medicare DRG systems were designed with the elderly Medicare population in mind. The APR-DRG system is more appropriate for obstetric, newborn, and pediatric care, which represent a substantial portion of Medi-Cal hospital visits (DHCS, 2014c).

Although the new DRG system was mandated in 2010, it was only implemented beginning with admissions on July 1, 2013 for private hospitals and with admissions on January 1, 2014 for non-designated public (NDP) hospitals. Once the new system was fully implemented, hospitals were no longer designated as contract or non-contract, HFPAs were no longer open or closed, and all private and NDP hospitals were subject to DRG-based reimbursement for inpatient services to Medi-Cal FFS enrollees. Table 2 below summarizes the number of hospitals that were subject to DRG implementation.

1.3. Outline

The remainder of this dissertation proceeds as follows. In Chapter 2, I provide a theoretical framework that provides motivation for the empirical questions addressed in subsequent chapters. In Chapter 3, I analyze the impacts of the California Medicaid hospital payment cut on hospital behavior. In particular, I study the impact of the Medicaid payment cut on access to care and intensity of care for both Medicaid patients and non-Medicaid patients. In Chapter 4, I estimate the impact of the introduction of DRG-based payments on hospital behavior. In Chapter 5, I summarize the results of these analyses and discuss policy implications.

1.4. Tables and Figures

Table 1: Medi-Cal Reimbursement System

	Closed HFPA (more competitive area)	Open HFPA (less competitive area)
Contract Hospitals	Negotiate per diem rate, can treat any Medi-Cal patients	Negotiate per diem rate, can treat any Medi-Cal patients (no clear reason to do this, very few)
Non-Contract Hospitals	Can only treat Medi-Cal patients if emergency or no other nearby hospitals	Paid a percentage of charges upfront, and then adjusted based on allowable costs

Table 2: Hospitals Subject to DRG Implementation

Hospital Type	Number of Hospitals	DRG Status
Private Hospital	352	Implemented July 1, 2013
Non-Designated Public Hospital	48	Implemented January 1, 2014
Designated Public Hospital	26	DRG not implemented

CHAPTER 2 : Conceptual Framework

In this chapter, I describe separate frameworks to conceptualize how hospitals may respond to payment reductions and to the introduction of DRG-based payments in theory. In both models, I consider how hospitals may respond to these payment changes in the way that they make admissions decisions and treatment decisions for patients. One concept I abstract from in these models is the link between hospital payments and the behavior of the individual physicians within those hospitals. Changes to hospital payments intended to change treatment patterns, such as bundled payments, pay-for-performance measures, or DRG payments all inherently assume that hospitals have some level of control over the decision-making of individual physicians acting within those hospitals. While changes to hospital payments have been shown empirically to elicit changes in treatment in various settings, the mechanism by which hospital boards or other hospital financial decision-makers may influence physician behavior is not explicitly modeled in this dissertation. Research on the hospital-physician relationship has noted that those who support hospital payment changes recognize the need for integration between hospitals' and physicians' goals for payment reform to be effective (Burns et al., 2010). The models presented in the following sections implicitly assume that hospitals exert some level of influence over physician behavior. However, it is true that a hospital cannot fully control the behavior of an individual physician, particularly those who are not employees of the hospital and only have admitting privileges. Among hospitals with less influence over physician behavior, or with a smaller proportion of employed physicians compared to physicians with admitting privileges, the response to hospital financial incentives intended to influence treatment or admissions behavior may be attenuated.

2.1. Hospital Response to Payment Cut

2.1.1. Intuition

The theoretical approach for this section focuses on how hospitals may respond to a payment reduction. In this subsection, I describe the intuition behind the theoretical predictions; the derivations are provided in the next subsection. I begin with a simple model of a profit maximizing hospital, and then expand the model to consider more complex responses. The profit maximizing hospital has two patient populations, which can be interpreted as a high-paying population of privately insured individuals, and a low-paying population of publicly insured individuals. The hospital can perfectly price discriminate between these two groups, and therefore the chooses quantity of care for each group such that price equals marginal cost. Then, if the public payer reduces its payment rates, the hospital responds by reducing the quantity of care provided to the publicly insured patients, while making no changes to care for privately insured patients. In this section, I derive predictions of hospital behavior for two payer types (which can be interpreted as a Medicaid-type payer, and a private insurer) because of the popularity in both the literature and among providers and insurers of the idea that a change in payments by a public payer can impact prices or care received by privately insured patients.

However, following previous theory, suppose that rather than being purely profit-maximizing, hospitals gain utility not only from profits, but also from the quantity of treatment provided to each group (Dranove, 1988). Then, if the public payer reduces prices, hospitals may respond in a number of ways based on their specific utility and cost functions. Hospitals will still respond by reducing the quantity provided to publicly insured patients, but not to the extent of the profit maximizing hospital, since they gain utility from providing care to these patients. In order to offset losses from this population, hospitals will also change the way they treat privately insured patients. The model predicts that unless a hospital sets quantity such that price equals marginal cost (i.e. unless the hospital is a profit maximizer), hospitals may respond to price reductions from the public payer by increasing quantity to the privately insured patients. The extent of this spillover effect is ultimately an empirical question determined by the specific functional forms of the utility and cost functions.

This model of hospital behavior under profit maximization indicates that in response to a payment decrease by Medicaid, pure profit-maximizing hospitals should simply reduce the quantity supplied to patients with Medicaid. However, if the hospital places some value on providing care to patients, it may be the case that either instead of or in addition to reducing the quantity provided to Medicaid patients by some amount, hospitals will increase the quantity provided to non-Medicaid, higher-paying patients. The potential responses I describe can be thought of as analagous to the income and substitution effects of a price change on an individual. The income effect may cause hospitals to reduce the amount of treatment for Medicaid patients, while the substitution effect may cause hospitals to respond by increasing the amount of care provided to higher paying patients. The intuition behind this model is that hospitals value more than profits alone, and in particular, value providing timely, appropriate care to patients. When a public payer cuts its payment rates, hospitals may not want to drastically reduce the quantity of care provided to affected patients. Instead, they may make more modest cuts to care for those patients, while seeking to make up the losses elsewhere. One way in which they may do this is by providing more care to more profitable patients.

This model focuses on hospitals' quantity responses, which brings up the following question: in the hospital setting, what does "quantity" mean? Broadly, quantity could mean two things: either the overall number of patients treated, or the "amount" or intensity of treatment patients receive in the hospital. Whether hospitals respond on the number of patients, amount of treatment, or both, as well as the extent of any change, remain empirical questions.

2.1.2. Derivation

Profit Maximizing Hospital

Suppose a hospital's objective function is as follows:

$$\pi = P_1 \cdot Q_1 - C_1(Q_1) + P_2 \cdot Q_2 - C_2(Q_2) \tag{2.1}$$

where P is price, Q is quantity, and $C(Q)$ is the cost function, and the subscripts 1 and 2 refer to groups of patients under two different insurers, where $P_1 < P_2$. Then, assuming the hospital is a price taker (which is fairly accurate in the case of Medicaid or Medicare), the first order conditions are as follows:

$$\frac{\partial \pi}{\partial Q_1} = P_1 - C_1'(Q_1) = 0 \tag{2.2}$$

$$\frac{\partial \pi}{\partial Q_2} = P_2 - C_2'(Q_2) = 0 \tag{2.3}$$

Profits are maximized when quantity is chosen such that $P_i = C_i'(Q_i)$, i.e. when price equals marginal cost for each patient group. Under the standard assumptions that $C'(Q) > 0$ and $C"(Q) > 0$, then $\frac{\partial Q_i}{\partial P_i}$ is positive, meaning that when the price decreases for either group, the hospital will reduce the quantity provided to that group in response, or in the extreme, cease supplying to that payer entirely. Since P_i does not enter into the equation of the optimal Q_j, when the price for group i changes, the optimal quantity for group j does not change.

Profit and Quantity Maximizing Hospital

Suppose that in addition to valuing profits, hospitals also gain utility through providing care to patients, as follows:

$$U = U\left(Q_1, Q_2; P_1, P_2\right) = \\ U\left(P_1 \cdot Q_1 - C_1(Q_1) + P_2 \cdot Q_2 - C_2(Q_2)\right) + U\left(Q_1\right) + U\left(Q_2\right) \quad (2.4)$$

where $U'(\pi) > 0$, $U''(\pi) < 0$, $U'(Q) > 0$, $U''(Q) < 0$, $C'(Q) > 0$, and $C''(Q) > 0$. Taking the first order conditions of equation 2.4 with respect to Q_1 and Q_2, I obtain:

$$\frac{\partial U\left(Q_1, Q_2; P_1, P_2\right)}{\partial Q_1} = f_1\left(Q_1, Q_2; P_1, P_2\right) = \\ U'\left(P_1 \cdot Q_1 - C_1(Q_1) + P_2 \cdot Q_2 - C_2(Q_2)\right) \cdot \left(P_1 - C'(Q_1)\right) + U'\left(Q_1\right) = 0 \quad (2.5)$$

$$\frac{\partial U\left(Q_1, Q_2; P_1, P_2\right)}{\partial Q_2} = f_2\left(Q_1, Q_2; P_1, P_2\right) = \\ U'\left(P_1 \cdot Q_1 - C_1(Q_1) + P_2 \cdot Q_2 - C_2(Q_2)\right) \cdot \left(P_2 - C'(Q_2)\right) + U'\left(Q_2\right) = 0 \quad (2.6)$$

Applying the implicit function theorem to the first order conditions above, I obtain:

$$\begin{pmatrix} \frac{\partial Q_1(P_1,P_2)}{\partial P_1} & \frac{\partial Q_1(P_1,P_2)}{\partial P_2} \\ \frac{\partial Q_2(P_1,P_2)}{\partial P_1} & \frac{\partial Q_2(P_1,P_2)}{\partial P_2} \end{pmatrix} = - \begin{pmatrix} \frac{\partial f_1}{\partial Q_1} & \frac{\partial f_1}{\partial Q_2} \\ \frac{\partial f_2}{\partial Q_1} & \frac{\partial f_2}{\partial Q_2} \end{pmatrix}^{-1} \begin{pmatrix} \frac{\partial f_1}{\partial P_1} & \frac{\partial f_1}{\partial P_2} \\ \frac{\partial f_2}{\partial P_1} & \frac{\partial f_2}{\partial P_2} \end{pmatrix} =$$

$$- \frac{1}{\frac{\partial f_1}{\partial Q_1}\frac{\partial f_2}{\partial Q_2} - \frac{\partial f_1}{\partial Q_2}\frac{\partial f_2}{\partial Q_1}} \begin{pmatrix} \frac{\partial f_2}{\partial Q_2} & -\frac{\partial f_1}{\partial Q_2} \\ -\frac{\partial f_2}{\partial Q_1} & \frac{\partial f_1}{\partial Q_1} \end{pmatrix} \begin{pmatrix} \frac{\partial f_1}{\partial P_1} & \frac{\partial f_1}{\partial P_2} \\ \frac{\partial f_2}{\partial P_1} & \frac{\partial f_2}{\partial P_2} \end{pmatrix} \tag{2.7}$$

The relationships of interest are $\frac{\partial Q_1}{\partial P_1}$ and $\frac{\partial Q_2}{\partial P_1}$, which describe how the quantity provided to groups 1 and 2 change when payer 1 (i.e. Medicaid) changes its price. Then, by equation 2.7, these relationships are defined as follows:

$$\frac{\partial Q_1 (P_1, P_2)}{\partial P_1} = -\frac{1}{\frac{\partial f_1}{\partial Q_1}\frac{\partial f_2}{\partial Q_2} - \frac{\partial f_1}{\partial Q_2}\frac{\partial f_2}{\partial Q_1}} \left[\frac{\partial f_2}{\partial Q_2}\frac{\partial f_1}{\partial P_1} - \frac{\partial f_1}{\partial Q_2}\frac{\partial f_2}{\partial P_1} \right] \tag{2.8}$$

$$\frac{\partial Q_2 (P_1, P_2)}{\partial P_1} = -\frac{1}{\frac{\partial f_1}{\partial Q_1}\frac{\partial f_2}{\partial Q_2} - \frac{\partial f_1}{\partial Q_2}\frac{\partial f_2}{\partial Q_1}} \left[-\frac{\partial f_2}{\partial Q_1}\frac{\partial f_1}{\partial P_1} + \frac{\partial f_1}{\partial Q_1}\frac{\partial f_2}{\partial P_1} \right] \tag{2.9}$$

The fraction in equations 2.8 and 2.9 expands to the following, where $U(P_1 \cdot Q_1 - C_1(Q_1) + P_2 \cdot Q_2 - C_2(Q_2))$ is shortened to $U(\pi)$ for brevity:

$$\frac{-1}{\begin{gathered} U"(\pi)\left\{-(P_1 - C'(Q_1))^2 C"(Q_2) U'(\pi) + U"(Q_2)(P_1 - C'(Q_1))^2 - \right. \\ \left. C"(Q_1) U'(\pi)(P_2 - C'(Q_2))^2 + U"(Q_1)(P_2 - C'(Q_2))^2 \right\} \\ +U'(\pi)\{U'(\pi) C"(Q_1) C"(Q_2) - C"(Q_1) U"(Q_2) - C"(Q_2) U"(Q_1)\} \\ +U"(Q_1) U"(Q_2) \end{gathered}} \tag{2.10}$$

Here, the fraction can be signed as negative based on the assumptions regarding the shapes of the utility and cost functions. The expression in brackets in equation 2.8 expands to:

$$U"(\pi)(P_2 - C'(Q_2))^2 U'(\pi) - C"(Q_2) U'(\pi) U"(\pi) \cdot Q_1 \cdot (P_1 - C'(Q_1)) \\ - C"(Q_2) U'(\pi)^2 + U"(\pi) \cdot Q_1 \cdot (P_1 - C'(Q_1)) U"(Q_2) + U'(\pi) U"(\pi) \quad (2.11)$$

Making the assumption that both expressions of the form $P - C'(Q)$ will be negative at the optimal Q_1 and Q_2 (given the utility function in equation 2.4), then the expression in equation 2.11 is negative based on the shapes of the utility and cost functions. Since the fraction in equation 2.10 is also negative, the sign of $\frac{\partial Q_1}{\partial P_1}$ is positive, meaning that when prices fall from payer 1, the quantity supplied to group 1 also falls, and vice versa.

To calculate $\frac{\partial Q_2}{\partial P_1}$, I expand the expression in square brackets in equation 2.9 to:

$$U"(\pi)(P_2 - C'(Q_2)) \{U'(\pi)(P_1 - C'(Q_1)) + U'(\pi) C"(Q_1) \cdot Q_1 - U"(Q_1) \cdot Q_1\} \quad (2.12)$$

Again assuming that both expressions of the form $P - C'(Q)$ will be negative at the optimal Q_1 and Q_2, the sign of the overall expression in equation 2.12 is ambiguous. This means that the sign of $\frac{\partial Q_2}{\partial P_1}$ is also ambiguous.

2.2. Hospital Response to Change in Payment Methodology

2.2.1. Intuition

The theoretical approach for this section focuses on how hospitals may respond to a shift to a new reimbursement methodology. In this subsection, I describe the intuition behind the theoretical predictions; the derivations are provided in the next subsection. I describe two types of hospitals—one that is paid on a FFS basis, and one paid on a per diem basis. Then, I describe how their incentives and behavior change when a DRG-based payment system in introduced. In modeling this behavior, I focus on hospitals' responses in the treatment of Medicaid patient only. While I study other patient types in the empirical analyses for completeness, the theoretical notion of a hospital responding to prospective payment by one payer by changing the treatment of other patients is much less popular in this literature than in the literature on hospital response to payment cuts.

Hospitals paid on a FFS basis get paid both for the treatment administered as well as per day of inpatient stay, so they choose treatment and LOS such that their prices equal their marginal costs. However, once DRG payments are introduced, hospitals don't receive payments based on specific treatments administered or length of stay. Instead, their incentive is to minimize treatment and length of stay subject to any minimum amounts they are legally required to provide. Therefore, it is expected that following the introduction of DRG payments, treatment intensity and length of stay should fall. However, it is possible that intensity and length of stay may remain relatively stable if under FFS payments, prices were relatively low, which in turn would imply low levels of treatment and length of stay even under FFS payments.

Hospitals paid on a per diem basis get paid per day of hospital stay, but do not get paid based on the treatment administered. Therefore, they choose length of stay such that its marginal cost equals its price, but seek to minimize the intensity of treatment, subject only to minimum levels of treatment required by law, fear of malpractice suits, or hospital goodwill. Furthermore, it may be the case that on average, for Medicaid patients (who are less likely to be in hospital for end-of-life care than Medicare patients), subsequent days of hospital stay require less treatment that the initial day.[4] Declining minimal treatment required gives an additional incentive for hospitals to increase length of stay. Once DRG payments are introduced, there is no major change in incentive when it comes to treatment intensity, given that hospitals already had an incentive to minimize intensity. However, the incentive when it comes to length of stay is completely reversed. It is expected that following the introduction of DRG payments, hospitals previously paid on a per diem basis should reduce average length of stay.

2.2.2. Derivation

Previous FFS Hospital

Suppose a hospital, paid on a FFS basis, has the following objective function:

$$\pi = P_T \cdot T + P_L \cdot L - C(T) - C(L) \tag{2.13}$$

where P is price, T is the "quantity" of treatment, L is the number of days of hospital stay, and $C(\cdot)$ is the cost function. Under a FFS payment scheme, a hospital would be paid separately for each treatment, as well as a "room and board" fee for the number of days of hospital stay. Then, assuming the hospital is a price taker (which is fairly

[4]For example, for patients admitted to the hospital for childbirth, the major cost comes on the first day when the delivery occurs, and subsequent days for recovery may require only minimal time with providers.

accurate in the case of Medicaid or Medicare), the first order conditions are as follows:

$$\frac{\partial \pi}{\partial T} = P_T - C'(T) = 0 \tag{2.14}$$

$$\frac{\partial \pi}{\partial L} = P_L - C'(L) = 0 \tag{2.15}$$

Profits are maximized when the quantities of treatment and days of stay are chosen such that their prices equal their marginal costs; hospitals have no incentive to cut back on services.

Now, suppose that the hospital is switched to a DRG-based payment methodology:

$$\pi = \bar{P} - C(T) - C(L) \tag{2.16}$$

For a given T and L it could be the case that $\bar{P} \leq P_T \cdot T + P_L \cdot L$ or $\bar{P} \geq P_T \cdot T + P_L \cdot L$. Therefore, I can only conclude that for services where prices on average decrease, the likelihood of admission may also decrease, and vice versa. However, in the empirical context of this research, predictions cannot be made about which direction this effect may go in overall. Taking the first order conditions of equation 2.16 gives:

$$\frac{\partial \pi}{\partial T} = -C'(T) = 0 \tag{2.17}$$

$$\frac{\partial \pi}{\partial L} = -C'(L) = 0 \tag{2.18}$$

This implies that hospitals now have incentive to keep the amount of treatment and the length of stay as low as possible, subject only to any constraints on the minimum level of care necessary to avoid lawsuits.

Previous Per Diem Hospital

Suppose now that a hospital was previously paid on a per diem basis, with the following objective function:

$$\pi = P_L \cdot L - C(T) - C(L) \tag{2.19}$$

where P,T, and L are as defined above, and $C(\cdot)$ is the cost function. Under a per diem payment scheme, a hospital would be paid per day of stay, but not per treatment.Then, the first order conditions are as follows:

$$\frac{\partial \pi}{\partial T} = -C'(T) = 0 \tag{2.20}$$

$$\frac{\partial \pi}{\partial L} = P_L - C'(L) = 0 \tag{2.21}$$

Here we see that the per diem hospital has an incentive to minimize T, again subject only to any constraints on the minimum amount of care necessary. However, the per diem hospital will choose L such that $P_L = C'(L)$.

Now, suppose that the hospital is switched to a DRG-based payment methodology:

$$\pi = \bar{P} - C(T) - C(L) \tag{2.22}$$

Again, for a given T and L it could be the case that $\bar{P} \leq P_L \cdot L$ or $\bar{P} \geq P_L \cdot L$. Therefore, I can only conclude that for services where prices on average decrease, the likelihood of admission may also decrease, and vice versa. However, taking the first order conditions of equation 2.22 gives:

$$\frac{\partial \pi}{\partial T} = -C'(T) = 0 \tag{2.23}$$

$$\frac{\partial \pi}{\partial L} = -C'(L) = 0 \tag{2.24}$$

Per diem hospitals already had an incentive to keep T as low as possible, and therefore I do not expect any change in behavior in terms of amount or itensity of treatment. However, when it comes to length of stay, the incentive is now reversed; per diem hospitals should reduce average length of stay once DRG payments are introduced.

CHAPTER 3 : Hospital Response to Medicaid Payment Cuts: Evidence from California

3.1. Introduction

Health insurance plans have long used supply-side financial incentives in efforts to slow health care cost growth. Changes in the level and structure of reimbursement are often used to align the incentives of providers and insurers, particularly within public insurance programs such as Medicaid. A simple way to attempt to change provider behavior is to reduce payments, which should theoretically cause a reduction in the quantity supplied. Lower quantities at lower prices should translate to savings for payers, but things are not always so straightforward in health care markets. For both legal and ethical reasons, providers may exhibit behaviors not consistent with profit maximization.

Over the past fifteen years, fiscally constrained state Medicaid programs have increasingly used hospital payment cuts as a policy lever to slow Medicaid spending growth. Economic downturns generally lead to an increase in the number of individuals who are eligible for Medicaid, which in turn worsens the burden on state budgets. Following the repeal of a requirement for "reasonable and adequate" payment rates for inpatient hospital services in 1997, it has become increasingly common for states to respond to this fiscal pressure by cutting or freezing Medicaid reimbursement rates to health care providers (Figure 1).[5] The incidence of payment cuts can be expected to grow if current trends continue; in 2015, 32 states restricted hospital payment through either payment freezes or cuts, up from 30 states in 2014 and 20 states in

[5] See Smith (2003, 2004, 2005, 2006, 2007, 2008, 2009) for detailed annual coverage of this issue.

2013.[6] While physicians may respond to low or decreasing Medicaid reimbursement rates by simply not accepting new Medicaid patients, it is infeasible for many hospitals, which operate at a much larger scale than most physician organizations, to forego admissions from the entire Medicaid population. Therefore, hospitals generally must respond to Medicaid fee decreases along other margins.

This chapter studies the extent to which hospitals may change patient care in response to a decrease in reimbursement by Medicaid. While it has become increasingly common for states to respond to fiscal pressure by cutting provider rates, the effects on treatment and access to care are not yet well understood. Policymakers often argue that there are inefficiencies in the health care system, and that cutting reimbursement will simply encourage providers to reduce the inefficiencies in their systems. However, it is not obvious that hospitals can or will respond in this way—if inefficiencies could easily be targeted and reduced, why would hospitals not already have done so? Hospitals are likely to continue seeing restrictions to payments by state Medicaid programs in the coming years. Quantifying the impacts of hospital payment cuts by Medicaid is therefore crucial to assessing whether taxpayers and policymakers are willing to make the tradeoff between reductions in Medicaid cost growth and potential changes to patient care.

Hospitals may respond to payment reductions by a public payer in a number of ways, but by far the most commonly studied outcome in the current literature has been cost shifting. Cost shifting refers to the notion that in response to a decrease in payments from a public payer, hospitals will increase prices to private payers. However, both theoretically and empirically, cost shifting appears to play at most a minimal role (Dranove, 1988; Morrisey, 1996; Frakt, 2011). A number of other

[6] Data kindly provided to the author by the Kaiser Family Foundation.

responses to payment changes are possible, such as overprovision of care to low-cost patients, underprovision of care to high-cost patients, or avoidance of high-cost patients (Ellis, 1998). Empirical work on these responses is limited, and existing research is largely focused on payment changes by Medicare (Dafny, 2005; White and Yee, 2013). However, it is not immediately clear that hospitals would have a similar response to payment decreases by Medicaid as they would to payment decreases by Medicare, highlighting a gap in the current literature (Gruber et al., 1999). Hospital response to broad Medicaid payment cuts is not yet well understood and research on responses other than cost shifting is limited.

In this research, I examine whether hospitals respond to Medicaid payment cuts by changing the way they provide treatment or control access to hospital care for patients, using a major decrease in Medicaid reimbursement rates in the state of California as a natural experiment. In 2008, the California Department of Health Care Services (DHCS) instituted a broad Medicaid payment decrease that affected about a third of the hospitals in the state. The cut amounted to at least a ten percent reduction in payment rates, a substantial decrease that affected reimbursement for acute care services provided to Medicaid fee-for-service patients by certain general acute care hospitals.[7] Given that prior to this reduction, hospitals typically saw modest annual increases to the reimbursement rate, I expect a priori that hospitals would have a strong response to such a large reduction in payments.

The state of California provides a particularly ripe setting for studying changes to Medicaid reimbursement, with one of the largest and most diverse Medicaid populations in the country (California HealthCare Foundation, 2009). Furthermore, California Medicaid was known for having some of the lowest reimbursement rates in the

[7] Some hospitals were exempt from this payment change. Reasons for exemption are detailed in Section 1.2.2.

country,[8] making it likely that reductions to already low reimbursement could have major impacts on hospitals.

I use a comprehensive hospital and emergency department discharge data set for the years 2007-2009 from the California Office of Statewide Health Planning and Development (OSHPD). Using a difference-in-differences approach, I measure the impact of the 2008 hospital payment reduction by Medicaid on both access to care and intensity of care for Medicaid patients. To test for spillover effects onto non-Medicaid patients, I also evaluate the impact of the Medicaid payment reduction on access to care and treatment intensity for Medicare and privately insured patients (White, 2013). To address concerns that treated and control hospitals may be differ substantially from one another, I analyze the same outcomes in a propensity score matched sample that mimics the difference-in-differences approach. These analyses provide a number of insights into hospitals' responses to cuts in Medicaid payment rates.

Contrary to conventional economic wisdom that a decrease in price would lead to a decrease in the quantity supplied, I do not find evidence supporting this behavior by hospitals. Across many measures of access to care and intensity of treatment, changes to Medicaid patients as a result of the Medicaid payment change are very small and not statistically significant. While I find some evidence suggestive of a spillover effect onto more profitable, non-Medicaid patients, these results do not persist in robustness checks. However, if it exists, an increase in intensity for non-Medicaid patients suggests that rather than responding to Medicaid payment cuts in the way they treat Medicaid patients themselves, hospitals responded by increasing the intensity of treatment for privately insured patients. This may occur if hospitals are trying to

[8] For example, in 2008, California Medicaid paid just 78% of the Medicaid national average for obstetric care (Zuckerman et al., 2009).

offset Medicaid losses with increased care to more profitable patients or are trying to attract more high-paying patients by providing “higher quality” care.

These findings have important policy implications. A reduction in prices to hospitals without an accompanying reduction in the amount of care provided indicates that the full cost-saving potential of this policy may not have been reached. Medicaid policymakers should consider whether other reimbursement incentives would be more effective in reining in Medicaid spending. Furthermore, policymakers should consider what spillover effects onto non-Medicaid patients may signal about a hospital. In the long term, hospital closures may be a concern hospitals are in financial distress. If this is more likely to occur among hospitals treating a high percentage of Medicaid patients, access to care for Medicaid patients could be seriously affected. Future work should further explore the potential spillover effects uncovered in this paper and examine the financial ramifications to Medicaid of hospital payment cuts. Provider payment cuts have become a frequently used policy tool, and therefore a clear understanding of the impacts of Medicaid payment cuts on Medicaid enrollees, non-Medicaid patients, and the Medicaid program itself is essential.

This research contributes to the literature in several ways. First, existing research on hospital response to payment changes has largely centered around relative changes in payment rates within the Medicare program, as opposed to the across-the-board cuts in Medicaid studied in this paper.[9] Second, there is a general paucity of research in the health economics literature regarding state Medicaid programs, as they generally pose a challenge in terms of institutional knowledge (Sommers, 2015). Finally, this research provides insight not only into how Medicaid patients might be affected by Medicaid payment cuts, but also how Medicare and privately insured patients are

[9] See Dafny (2005); Eldenburg and Kallapur (1997); Lindrooth et al. (2007); White (2013); White and Yee (2013); White and Wu (2014).

affected.

3.2. Empirical Approach

3.2.1. Outcome Measures

1. **Access to care** is measured in two ways:

   (a) First, the *likelihood of admission* is defined as the likelihood of inpatient admission to the hospital following a visit to the same hospital's emergency department.

   (b) Second, *hospital-level insurance mix* is defined at the hospital level as the proportion of Medicaid FFS patients divided by the total population of patients.

2. **Intensity of care** is measured in a number of ways:

   (a) First, it is measured as the *length of stay (LOS),* which is included in each hospital discharge record.

   (b) Second, it is measured as the *total charges associated with the discharge*, with the assumption that higher charges generally imply more intense care.

   (c) A third measure of intensity of care is measured as the *number of procedures* associated with the discharge (under the assumption that a greater number of procedures generally implies more intense care).

   (d) Finally, I also conduct analyses among a subset of patients for whom defining intensity of care is much more straightforward—women admitted to the hospital for childbirth. Childbirth is an ideal setting to study intensity of care, since there are essentially only two options for care (vaginal delivery or delivery via cesarean section), and one (and only one) of those is associated with every delivery. Furthermore, childbirth is commonly used in the literature to study intensity of care because as previous work has noted, the underlying costs in terms of physician time are considered similar between cesarean section and vaginal delivery, but cesarean section is typically reimbursed at a higher rate (Gruber et al., 1999). Finally, childbirth is particularly useful to study in the context of this research since it is a very common reason for hospital admissions among the Medicaid population. Therefore, among the cohort of women admitted to the hospital for childbirth, I also measure the *likelihood of receiving a cesarean section.*

3.2.2. Identification Strategy

To identify the effects of the reimbursement rate reduction, I include only hospitals within open HFPAs in my sample, since treated hospitals in closed HFPAs would have mechanically had very low proportions of Medicaid FFS patients, and therefore may not have had major response to the fee decrease. Non-contract hospitals subject to the payment cut make up the treated group, and all remaining hospitals in open HFPAs that were not subject to this payment change make up the control group.

When choosing hospitals to include in the control group, there were three potential groups of hospitals to consider:

- Non-contract hospitals that were exempt from the fee decrease because they qualified as "small or rural" hospitals
- Non-contract hospitals that were exempt from the fee decrease because the HFPA to which they belonged had fewer than three total hospitals

- Contract hospitals

Arguments could be made as to why each of these groups would or would not make appropriate comparison groups for the treated hospitals. Overall, recall that open and closed HFPAs were grouped as such due to the level of competition in the market, so one can at least say that the level of competition each of these hospitals faces is similar. More specifically, small or rural hospital status is given to hospitals that meet at least one of the following criteria: have 100 or fewer beds, have 4000 or fewer admissions, or are located outside a Metropolitan Statistical Area. For all of these criteria, it is likely that many hospitals that are in open HFPAs (already more rural, less densely populated parts of the state) that do not actually qualify as small or rural may have "just missed" qualifying for this status and therefore may not be inherently different from those that did qualify. In terms of the number of hospitals in the open HFPA, the data shows that within an open HFPA, the number of hospitals ranges only from one to five. Hospitals in HFPAs with three or four hospitals may not differ greatly from hospitals in HFPAs with one or two hospitals. Finally, one might argue that hospitals that willingly contract with Medicaid when there is no incentive to do so must differ from hospitals that do not contract. However, anecdotal evidence shows that hospitals that contract in open HFPAs generally do so because they are a part of a larger hospital system where many of the other hospitals are in closed HFPAs, so the hospital in the open HFPA contracts only for administrative ease with the rest of the system. Furthermore, for the most part, contracting status was chosen in the 1980s and not changed, making this an almost exogenous factor. These three types of potential control hospitals make up a group that is reasonably similar to the hospitals in the treated group, and I therefore include them all in the control group.

One concern with these analyses is that a number of counties in California had Medicaid managed care plans that were mandatory for most non-elderly, non-disabled enrollees. This would imply that for most Medi-Cal enrollees in these counties, the 10% fee decrease would not have applied. However, by the end of the study period, 33 of the 58 counties in California still had no managed care plans at all, and even hospitals in counties that offered managed care may have seen substantial numbers of patients from neighboring counties. Furthermore, upon first enrollment in Medicaid, all patients, regardless of county, are enrolled in FFS for the first 30 days. Given that many uninsured patients are enrolled in Medicaid upon presentation in an emergency department or hospital, this may impact the proportion of Medicaid FFS patients a given hospital sees. Therefore, to ensure that the hospitals included in the sample would have felt real impacts of the Medicaid FFS payment cut, I simply use cutoffs based on the hospital's lagged share of Medicaid FFS patients. Using the percentage of Medicaid FFS patients in hospitals in counties that did not offer managed care as a benchmark, I use a cutoff of 10% in my analyses.[10]

Finally, in the analyses studying the likelihood of hospital admission for patients appearing in the ED, it may be unlikely to see a response across all reasons for ED visit. For example, in the case of an immediate life-threatening emergency, it is unlikely (and illegal) for hospitals to refuse to treat a patient based on insurance status (CMS, 2012). Therefore, in addition to looking at overall ED visits, I also examine ED visits broken down into visits considered to require emergency care, versus those that are primary care treatable or non-emergent, using an ED classification algorithm developed by researchers at New York University (Billings et al., 2000). The algorithm provides a percentage of cases for a given diagnosis that are considered *non-emergent* (ED care not needed), *emergent but primary care treatable* (ED care not needed),

[10]Sensitivity analyses around this cutoff were conducted, and did not change the results of the study.

emergent but preventable (ED care needed), and *emergent and not preventable* (ED care needed). I break up the sample into ED visits with a non-zero proportion of "ED care not needed" versus those with a non-zero proportion of "ED care needed."[11]

3.2.3. Sample Selection

A sample selection flowchart is provided in Figure 3. The sample of hospitals was limited to those in open HFPAs only, and further to hospitals with at least a ten percent share of Medicaid FFS patients in the pre-period. Additionally, I drop hospitals with fewer than 500 admissions in either the pre- or post-periods, and hospitals that were run by a city, county, or district.[12] This resulted in a sample of 12 treated hospitals and 37 control hospitals.[13] For sample selection of patients, only patients insured by Medicaid FFS, Medicare, or private insurance were included in the sample. Patients for whom certain variables (age, race, gender, or admission source) were missing were excluded from the analysis. Finally, patients with very uncommon conditions or who were extreme outliers in LOS or charges were excluded from analysis as well, leading to a final sample of 704,312 patients.

3.2.4. Difference-in-Differences Analysis

I utilize patient discharge data and emergency department data from quarter 1 of 2007 to quarter 3 of 2009. The reimbursement rate decrease took effect in July 2008, so this provides six quarters of pre-data and five quarters of post-data. I use the end of Q3 2009 as the end of my study period for several reasons. First of all, given the magnitude of the rate cut, I expect that any potential hospital response would be

[11] These are not mutually exclusive categories. However, this is the broadest way to classify the data without introducing arbitrary cutoff points.

[12] These hospitals were dropped because they only appeared among the control group.

[13] Statistical power issues were generally not a concern, as most analyses are done at the patient level.

observed soon after the policy was enacted. More importantly, I specifically end my study period at the end of Q3 2009 rather than the end of 2009 due to a lawsuit filed by several non-contract hospitals which resulted in a preliminary injunction being issued in November 2009 that prohibited the DHCS from continuing to apply the ten percent reduction in allowable costs to the plaintiff hospitals (DHCS, 2009). However, the existence of this lawsuit indicates that the rate cut was more than just superficial, and provides anecdotal evidence that the rate cut likely had real impacts on hospitals. Prior to the 2008 cut, hospital reimbursement rates had been increasing nominally each year.

I use a difference-in-differences approach to compare access to care and intensity of care in hospitals that were subject to the fee cut versus those that were not, prior to and following its 2008 implementation. The regression is specified as follows:

$$Y_{ijtk} = \beta_0+\beta_1\cdot Post_t+\beta_2\cdot Treated_j+\beta_3\left(Post\times Treated\right)_{tj}+\beta_4\cdot\mathbf{X_i}+\beta_5\cdot\mathbf{Z_j}+\beta_6\cdot\mathbf{W_k}+\varepsilon \tag{3.1}$$

where Y is the outcome of interest. $Post$ indicates the admission occurred at time t following the fee decrease, $Treated$ indicates that hospital j was subject to the fee decrease, and $Post\times Treated$ is the interaction of the two. $\mathbf{X}$ is a vector of patient-level covariates for patient i, $\mathbf{Z}$ is a vector of hospital level covariates for hospital j, and $\mathbf{W}$ is a vector of county-level covariates for county k. Patient level demographics include age, gender, ethnicity (Hispanic or non-Hispanic), and race. Additionally, patient health characteristics associated with the admission are included. Hospital level covariates include the profit status of the hospital (for profit vs. not-for-profit) and the pre-payment change Medicaid FFS proportion of patients. County level characteristics include the county-level Medicaid FFS proportion, the unemployment rate, and average income. For continuous outcomes (i.e., charges), the equation is estimated via linear regression. For count outcomes (i.e., length of stay, number of procedures), the equation is estimated using Poisson regression. Finally, to estimate event likelihood (i.e., likelihood of admission, likelihood of c-section), I use logistic regression. The analyses are done separately for Medicaid fee-for-service patients (primary effect), and then for Medicare or privately insured patients to test for secondary effects. Standard errors are cluster robust, with clusters defined at the hospital level (Bertrand et al., 2004).

To understand the impact of the fee cut on the hospital-level mix of patients by insurer type, I estimate the following equation:

$$Y_{jtk} = \beta_0 + \beta_1 \cdot Post_t + \beta_2 \cdot Treated_j + \beta_3 \left(Post \times Treated\right)_{tj} + \beta_4 \cdot \mathbf{Z_j} + \beta_5 \cdot \mathbf{W_k} + \varepsilon \quad (3.2)$$

where the outcome Y is the proportion of Medi-Cal FFS patients, defined at the hospital level. Since discharges are on the quarter-year level, each hospital has one observation per quarter-year. I use heteroskedasticity robust standard errors.

3.2.5. Propensity Score Triple Matching

One issue that may be raised with a difference-in-differences strategy is that it may suffer from bias if hospitals subject to the fee decrease differ in unobservable ways from hospitals not subject to the fee decrease. Therefore, as a sensitivity analysis, I also conduct these analyses using a matched sample approach. While matching does not explicitly control for omitted variable bias, it excludes control hospitals or patients that are "too different" from treated units on observable characteristics. Matching also has the desirable property of not relying on the correct specification of functional form (Zanutto, 2006).

For the analyses of length of stay, intensity of care, and likelihood of admission (i.e., the discharge-level analyses), I adapt a triple matching procedure which allows me to implement a propensity score matching procedure while utilizing the variation found in the difference-in-differences approach (Hansen, 2007; Rosenbaum, 2002). The match ensures that pre-treatment characteristics are similar, implying that any post-match differences can be attributed to the policy change. The first step in this approach is to match each treated hospital to a control hospital based on pre-treatment hospital characteristics. Then, within each hospital, a patient from the pre-period is matched to a patient from the post-period. Finally, the matched patient pair from a treated hospital is matched to a patient pair from the hospital's matched control, resulting in a patient quadruple similar to the basis for a difference-in-difference analysis. Each level of matching is carried out using a propensity score matching technique. For the hospital-level match, the propensity score is estimated using logit regression as the predicted probability of a hospital being subject to the fee decrease:

$$Pr(FeeCut = 1) = \beta_0 + \beta_1 \cdot \mathbf{Z_j} + \beta_2 \cdot \mathbf{W_k} + \varepsilon \tag{3.3}$$

where $\mathbf{Z_j}$ are hospital characteristics, including the proportion of Medicaid discharges, number of total discharges, and average available beds, and $\mathbf{W_k}$ are county-level characteristics, and include unemployment rate, average income, and the proportion of county residents eligible for Medicaid FFS. Next, I construct the within-hospital match of patients:

$$Pr(Post) = \beta_0 + \beta_1 \cdot \mathbf{X_i} + \varepsilon \tag{3.4}$$

In the estimation of the propensity score, I include the following patient-level covariates on the right-hand side: diagnosis, age, gender, race, and source of admission. Once pre-post matched pairs are constructed within each hospital, the average of the covariates for each pair is calculated, and then each pair in a treated hospital is matched to a pair in the control hospital with the propensity score estimated as in equation 3.4. I use 1:1 propensity score caliper matching throughout, because any larger number of controls to treated units would result in large numbers of observations needing to be discarded.

I use a random effects model to estimate the results:

$$Y_{ijtk} = \beta_0 + \beta_1 \cdot Post_t + \beta_2 \cdot Treated_j + \beta_3 \left(Post \times Treated\right)_{tj} + \varepsilon \tag{3.5}$$

This allows me to utilize the systematic bias introduced by matching by using the matched group identifier as the group variable in the regression. Similar to the unmatched difference-in-differences regressions, I use linear regression for continuous variables, Poisson regression for count variables, and logistic regression for binary variables.

3.3. Data Sources

I use discharge-level, hospital-level, and county-level data. The discharge data includes information on patients discharged from both hospitals and emergency departments (EDs), and includes patient characteristics as well as diagnosis and treatment variables. Hospital-level variables include both general hospital characteristics, as well as more specific information regarding SPCP contracting status and HFPA area status. Finally, county-level variables include variables on county-level unemployment, income, and Medicaid penetration rates. The sources for each of these are described in more detail in the following subsections.

3.3.1. Patient-Level Variables

Patient Discharge Data

Patient-level discharge data come from the California Office of Statewide Health Planning and Development (OSHPD) for the years 2007 to 2009. I use the non-public use versions of the inpatient discharge data and the emergency department data to ensure full access to demographic variables. The inpatient discharge data include a record for every inpatient discharge from a California-licensed hospital. Each record consists of the hospital at which care was received, date of birth, gender, ethnicity, race, principal language spoken, county of residence, zip code, admission date, discharge date, length of stay, source of admission (own hospital ED, other hospital ED, no ED), disposition, expected source of payment (Medicare, Medi-Cal, private coverage, etc), type of coverage (traditional FFS, managed care, etc), total charges, major diagnostic category (MDC), CMS Diagnosis Related Group (DRG), principal diagnosis, other diagnoses, principal procedure, and other procedures. I control for diagnoses by using the DRG grouping.

Emergency Department Data

Patient-level emergency department data for the years 2007 to 2009 also come from OSHPD. The ED data include a record for every ED encounter that involved face-to-face contact with a provider at a hospital licensed to provide emergency medical services. Patients who left the ED without being seen are not included in the data. The ED data include variables on the facility at which emergency care was sought, the patient's date of birth, gender, ethnicity, race, principal language spoken, county of residence, zip code, service date, disposition, expected source of payment, principal and other diagnoses, and principal and other procedures. Since DRGs are not included in the ED data, I use the Clinical Classifications Software, a diagnosis-grouping algorithm, in order to cluster diagnoses into clinically meaningful categories (Elixhauser et al., 2014). It is also important to note that in analyses using the ED data only, I can only observe the payer category (Medicare, Medi-Cal, private coverage, etc.), but not the type of coverage (managed care vs. FFS). Therefore, I include all Medi-Cal patients in the analyses.

3.3.2. Hospital-Level Variables

Basic hospital-level variables were found in the OSHPD data. This includes a unique hospital identification number and hospital name, hospital zip code, hospital county, and the total number of discharges by year. Additional hospital-level variables are described below.

Information on the contracting status of each hospital, as well as the area status (open or closed) of the HFPA in which the hospital is found, was hand-collected from a number of sources. The HFPA to which each hospital was assigned was found in hospital financial reports that are publicly available from OSHPD.[14] These reports also denoted whether a hospital was considered a small or rural hospital (small and rural hospitals were exempt from the 2008 fee decrease). HFPA area status (closed or open) was found in the California Medical Assistance Commission (CMAC) Annual Reports to the Legislature (2009-2010).[15] Finally, the contracting status of each hospital came from the CMAC reports and individual annual hospital financial disclosure reports publicly available from OSHPD.[16]

[14] http://www.oshpd.ca.gov/hid/Products/Hospitals/QuatrlyFinanData/CmpleteData/default.asp
[15] http://www.dhcs.ca.gov/services/spcp/Pages/default.aspx
[16] https://siera.oshpd.ca.gov/FinancialDisclosure.aspx

The hospital-level data set was then constructed as follows: all hospitals that appeared in the OSHPD discharge data were identified, and then hospitals that did not appear in all three years of data were excluded. Additionally, all hospitals that were not general acute care hospitals were excluded from the analysis. HFPA status, HFPA area status, and contracting status variables were then merged into the hospital data. There were a small number of hospitals for which contracting status could not be identified, so records from these hospitals were excluded. There were also a small number of hospitals that changed contracting status during the study period, and were therefore excluded.

3.3.3. County-Level Variables

County-level variables are included in regression analyses to control for any differential impacts of the 2008 economic recession, and include Medi-Cal fee-for-service penetration rates, unemployment rates, and income levels. Medi-Cal penetration rates come from publicly available Medi-Cal eligibility and enrollment statistics which are available by year and county.[17] County-level unemployment statistics come from the Bureau of Labor Statistics Local Area Unemployment Statistics.[18] These data include monthly county-level unemployment rates, and were merged into the OSHPD patient discharge data based on hospital county. Finally, county-level income levels come from the U.S. Census Bureau Small Area Income and Poverty Estimates.[19] These data include annual county-level income rates, and were merged into the OSHPD patient discharge data based on hospital county.

[17] dhcs.ca.gov/dataandstats/statistics/Pages/RASD_Enrollment_by_Geographic_Region.aspx
[18] bls.gov/lau/data.htm
[19] census.gov/did/www/saipe/index.html

3.4. Results

3.4.1. Descriptive Statistics

Descriptive statistics of the hospitals included in the analysis are presented in Table 3. A total of 12 treated hospitals and 37 control hospitals met the inclusion criteria for the analysis. Treatment hospitals were generally larger than control hospitals, with roughly twice as many total discharges and twice as many total hospital days in 2007. This is likely due to the fact that hospital size in part determined exemption from the reimbursement cut, and it should therefore be expected that control hospitals are smaller that treatment hospitals. However, both treated and control hospitals had similar proportions of patients covered by Medi-Cal FFS, with nearly a quarter of patients on average covered by Medi-Cal FFS.[20]

Descriptive statistics of Medicaid FFS patients are presented in the left four columns of Table 4. Among the Medicaid FFS population, average age is 23-24 years old and over two-thirds are female, with little variation between treatment/control hospitals or pre/post periods. Control hospitals see a more predominantly white Medicaid population (more than 75% white), while treatment hospitals have a Medicaid population that is about 60% white, with the difference largely attributable to more patients of "other" race. Average charges appear stable among patients in treated hospitals, while increasing slightly among patients in control hospitals. Within the cohort of women admitted to the hospital for childbirth, there is little change in the proportion of women receiving a cesarean section compared to vaginal birth. There is also very little change in the proportion of patients admitted to the hospital given

[20]Recall that these are hospitals in less wealthy, more rural areas of the state, and that over half of CA counties at this time did not offer Medicaid Managed Care plans. In addition, hospitals with less than a 10% Medicaid FFS share were excluded from analyses.

an appearance in the ED.

Descriptive statistics of Medicare and privately insured patients are presented in the right four columns of Table 4. These patients are on average older than Medicaid patients (due to the Medicare population), but there are no major changes in age over time. Almost 60% of patients in both treated and control hospitals are female, and similar to the Medicaid population, a higher proportion of patients in control hospitals are white, likely attributable to geographic differences in treated and control hospitals. In both treated and control hospitals, there is very little change in inpatient LOS. There is a small increase in mean charges and a small decrease in the average number of procedures in both treatment and control hospitals. Where the descriptive results may point to a potential spillover effect of the policy, however, is in the likelihood of receiving a c-section and the likelihood of admission to the hospital. Among privately insured women, the percentage receiving a c-section in treated hospitals increases by two percentage points, while no change was observed in control hospitals. Similarly, the percentage of patients admitted to the hospital given an ED visit increases by about two percentage points in treated hospitals following the policy change, while remaining the same in control hospitals.

The descriptive statistics are suggestive of a spillover effect, but highlight the need for regression analyses controlling for potential confounders.

3.4.2. Access to Care

The plots in Figure 4 present the difference-in-differences plots of access to care measures. The top pair of plots shows the trends in likelihood of hospital admission over time among both Medicaid patients and Medicare/privately insured patients. Based on the plots alone, it appears that after the Medicaid payment decrease, the likelihood of hospital admission given an ED visit decreases for both Medicaid patients and Medicare or privately insured patients in treated hospitals compared to control hospitals. Table 5 presents the results of the difference-in-differences logistic regression on the likelihood of hospital admission.[21] The coefficient on $Post \times Fee\,Cut$, presented as an odds ratio (OR), is the coefficient of interest. The results show that in response to the Medicaid reimbursement cut, the likelihood of admission falls slightly among Medicaid patients (OR = 0.996), and increases slightly among Medicare and privately insured patients (OR=1.013), but the coefficients are not statistically significant. This suggests that it is unlikely that hospitals are systematically responding to Medicaid reimbursement cuts by changing their criteria for hospital admission from the ED. To address concerns that all ED visits may not be responsive to changes in reimbursement, I also examine the results broken down by visits that were considered "ED Care Needed" versus visits that were considered "Primary Care Treatable" or "Non-Emergent." One might expect that there would be little response to payment changes among ED visits that are truly emergencies, but that there may be more movement among visits that did not require emergency services. Table 6 presents the results; even broken down by severity of ED visit, there is little movement in the likelihood of admission for either Medicaid patients or Medicare/privately insured patients.

The bottom plot in Figure 4 presents the difference-in-differences plot of hospital proportion of Medicaid FFS patients over time; no clear pattern is evident. In the regression analysis presented in Table 7, the coefficient of interest is in the expected direction (-0.01), but is not statistically significant. However, these results may be noisy given the relatively small sample of hospitals.

[21] Note that in all regression tables, coefficients on individual diagnoses-level controls have been omitted for brevity.

In both analyses, the results are in the expected direction, but are not statistically significant. The results of these analyses together suggest that access to care may not suffer significantly for Medicaid patients following a Medicaid reimbursement decrease to hospitals. Further, there is no evidence of increased admissions of patients with higher paying insurers.

3.4.3. Intensity of Care

To study the impact of the Medicaid payment cut on intensity of care, I study a number of measures of inpatient intensity of care. The plots in Figure 5 illustrate the existence of pre-policy parallel trends in outcomes. Table 8 presents the results of the difference-in-differences analysis of the impact of the Medicaid payment cut on inpatient length of stay. In both the Medicaid cohort as well as the cohort of Medicare or privately insured patients, the coefficient of interest is very small and not statistically distinguishable from zero. This failure to reject the null implies that it is unlikely that hospitals respond to Medicaid payment cuts by altering average length of stay. This is perhaps not a surprising result in the context of this paper, given that California is already known to have a relatively short length of stay on average, compared to other states (California HealthCare Foundation, 2010). Table 9 similarly shows little evidence of a primary or spillover effect of the Medicaid payment change on hospital charges. Table 10 presents the results on the number of procedures associated with each discharge. Similar to the other measures of intensity of care, the size of the coefficients on $Post \times Fee\,Cut$ are very small, and not statistically different from zero for both the Medicaid and the Medicare/privately insured populations. These results together would suggest that the hospitals in this study do not appear to react strongly to Medicaid payment cuts on the margin of intensity of care.

Table 11 presents the results of the logistic regressions on the likelihood of childbirth via cesarean section among the cohort of women admitted to the hospital for childbirth. Similar to the other measures of intensity of care, there is little response to the payment decrease on the likelihood of receiving a c-section among the Medicaid population. However, the odds of a privately-insured woman receiving a c-section increased by 12.5% ($p<0.01$). This implies a spillover effect of the Medicaid payment decrease onto privately insured women, indicating that to make up losses from the Medicaid population, hospitals may be increasing intensity of care to privately insured patients. Although the results from the other measures of intensity of care were not statistically significant, the results from the birth analysis represent the most accurate measure of intensity of care. It may also be the case that this increase in intensity of care is only possible or feasible in certain inpatient settings, and when studying a broad set of diagnoses as with the other measures of intensity of care, these effects are obscured. Finally, it should be noted that for the other measures of intensity of care, hospitals have no incentive to provide more services or more intense care (controlling for the DRG) when paid prospectively, as they are paid by Medicare, and most private insurers. Therefore, a lack of significant findings for the Medicare and privately insured population for the other measures of intensity is unsurprising. Hospitals do however, generally get paid more for c-sections compared to vaginal deliveries.

3.4.4. Results from Matched Analysis

Table 12 presents a table of standardized differences in covariates prior to and following the propensity score matching procedure on hospitals. Generally, standardized differences of lower than 0.2 imply acceptable covariate balance. Standardized differences below or around 0.2 are achieved for all covariates, and those that are slightly above 0.2 are generally a strong improvement over the unmatched sample. Figure 6 plots the distributions of hospitals' propensity to be subject to the payment reduction among treated hospitals, among all control hospitals, and among matched control hospitals. While the range of support for the treated hospitals is wider than that of the potential control hospitals, it is clear that the matched control sample has a much closer distribution of propensities than the overall group of control hospitals.

In general, the results from the matched analyses are similar to the results from the unmatched difference-in-differences analyses, indicating that the difference-in-differences setup was well designed to control for confounders. However, there are some differences to note. First, in the analysis of likelihood of hospital admission, the results of the matched analysis imply that as a result of the Medicaid payment cut, hospitals are significantly more likely to admit both Medicaid patients (OR=1.193, $p<0.001$) and Medicare or privately insured patients (OR=1.054, $p<0.01$). Among the intensity of care measures, length of stay and charges continue to have very small, and statistically non-significant effects (as in the unmatched difference-in-differences analyses). However, in the matched analysis of number of procedures, the result becomes slightly significant for the Medicare/privately insured population, implying that as a result of the Medicaid payment cut, Medicare or privately insured patients saw a 1.8% increase in the number of procedures per admission ($p<0.05$). This effect is small and only mildly significant.

However, in the matched analysis, while privately insured women are still more likely to receive a c-section in treated hospitals after the Medicaid payment change, the result is no longer statistically significant. Given that this is the only significant result in the main analyses, I conduct some further analyses to help determine the true nature of the effect. If the likelihood of c-section truly increased, then there should be corresponding increases in the length of stay and charges among the birth population, since c-sections are on average associated with longer inpatient stays and higher charges. Running these analyses on the original, unmatched sample, I find no significant changes in length of stay or charges among the birth cohort, leading to the conclusion that any real changes in the likelihood were minimal at best.

3.4.5. Additional Analysis

Robustness Checks

1. I conduct sensitivity analyses to determine whether the results are robust to the 10% Medicaid FFS proportion cutoff that I introduce in my sample selection procedure for hospitals. Varying this cutoff down to 5% and up to 15% does not have any major impacts on the results.

2. I also run these analyses under other specifications, including using a quarter-year fixed effect rather than a pre/post dummy, and using a hospital fixed effect rather than a treated/control dummy. These alternate specifications also did not alter the results substantially.

Subgroup Analysis of Uninsured Population

In my exploration of potential spillover effects of the Medicaid fee cut, I focus on spillover effects onto Medicare and privately insured patients, who make up the largest population of non-Medicaid patients. However, one might expect spillover effects, if any, to be strongest among the uninsured population. Due to difficulty identifying uninsured patients in the OSHPD data, I do not include them in the main analyses. However, I do conduct analyses on the patient population identified in the data as having a payer type of "county indigent program," "other indigent," or "self-pay," which is the closest approximation of uninsurance. In these analyses, I find no significant impacts of the Medicaid fee cut on any of the measures of access to care or intensity of care that I study in this chapter. However, it is difficult to draw inferences from these results, as it is not clear how accurately the uninsured population was identified.

3.5. Policy Implications and Discussion

3.5.1. Policy Implications

Following the Balanced Budget Act of 1997, it has become increasingly common for states to use provider payment cuts in an attempt to control Medicaid cost growth. This is likely to become even more commonplace if recent trends continue. This research finds no evidence to support the economic intuition that in response to Medicaid payment cuts, Medicaid patients should see reductions to their access to care or intensity of care in the hospital setting. This would suggest that from Medicaid's perspective, in the face of state budgetary issues, hospital payment changes may be preferable to broader changes in eligibility for Medicaid or generosity of coverage. However, it may be the case that a larger reduction to payments may have had more dramatic effects on patient treatment. Policymakers should also take into consideration that the lack of hospital response to the Medicaid payment cut means that rather than a reduction in both quantity and price, the reduction in price alone would lead to a smaller reduction in spending from Medicaid's perspective.

Policymakers should also take into consideration other ways that hospitals may respond to financial distress caused by payment cuts. In particular, financial distress may be expressed in ways not studied in this dissertation. Cuts to hospital staff, cutting unprofitable services, or at the extreme, hospital closures could all occur in response to financial distress caused by Medicaid payment reductions. This could indirectly impact quality of care and access to care for Medicaid patients in the long run, and future work should focus on studying these potential responses over a longer time horizon.

3.5.2. Discussion

Despite the increasing use of provider payment cuts in efforts to slow Medicaid cost growth, prior to this work, little was known about how hospitals may respond to such payment cuts. Contrary to model predictions and conventional economic thought, as well as previous work on Medicare hospital payments (White, 2013), this research finds no evidence to support the notion that hospitals would reduce the quantity of care supplied to Medicaid patients in response to a decrease in Medicaid prices. However, I evidence suggestive of increased intensity of care to privately insured patients in response to the Medicaid payment decrease, implying a spillover effect by which hospitals seek to make up losses from lower Medicaid prices by increasing services to higher-paying patients. These findings are suggestive that hospitals may be unwilling to reduce the level of treatment or reduce access to care even in the face of a large payment reduction for a given population, but may attempt to make up for those losses by increasing intensity of care to higher-paying patients.

Although this paper does not find evidence that hospitals reduce access to care or intensity of care to Medicaid patients in response to Medicaid payment cuts, this finding is consistent with prior research that finds that hospitals lean toward administrative changes rather than changes to patient care in response to relative changes to payments (Dafny, 2005). This could imply that in general, hospitals' roles as agents for their patients lead them to seek other, non-care related ways to make up for losses in payment. Furthermore, while the physicians in charge of individual patients' care decisions may be less concerned with general hospital finances, those making decisions on general offerings of services, the amount of uncompensated care provided, or other administrative decisions are likely to be the same individuals concerned with the hospital's financial status.

There may be several other explanations for the results found in this research. The hospitals in this study may have had some capacity to bear payment reductions without drastically changing patient treatment, so it is possible that the 10% payment reduction studied in this research was not large enough to cause dramatic changes. In the same vein, there may also be discontinuities in the response to payment reductions whereby the magnitude of the response to the reductions studied in this research were small, but could increase drastically with a small increase in the size of the payment decrease. It is also important to note that this research specifically focused on spillover effects to Medicare or privately insured patients, but it has been posited in the literature that hospitals may respond to payment cuts by limiting the amount of uncompensated care they provide (Morrisey, 1996; Altman et al., 2006). While I attempt to address this issue, the data used for this research do not allow for clear identification of uncompensated care, and therefore making inferences based on the results is difficult. While some existing empirical work has failed to find evidence of this hypothesized effect in the Medicare setting, future work should focus on addressing this question in the Medicaid setting (Cutler, 1998).

It should also be noted that this research is not comprehensive in its study of the potential responses of hospitals to Medicaid payment decreases; rather, this study focused specifically on hospital response to Medicaid payment cuts along the patient care margins of access or intensity of care. In general, hospital financial distress caused by a Medicaid payment cut may be expressed in other ways, such as physician time per patient, hospital staffing, or the purchase of new equipment. In particular, prior work has found some evidence that hospitals may reduce their offerings of less profitable or unprofitable services in response to negative financial shocks (Dranove et al., 2013). At the extreme, hospital financial distress could also lead to hospital closure. Especially among hospitals with larger proportions of Medicaid patients, this could be a serious consideration for policymakers concerned with access to care for Medicaid patients. Future research should explore these other potential responses.

Some limitations should be taken into account when considering the results of this study. First, the study is focused on a subset of hospitals within California. A problem inherent to studying Medicaid is that Medicaid programs differ from state to state, and a study of one state's program may not be nationally generalizable. However, California has one of the largest Medicaid populations in the country, serving 16% of the non-elderly population in the state, and also has a demographically diverse Medicaid population. Furthermore, despite the limited generalizability of the specific institutional details, this study still has important implications for how hospitals may respond to Medicaid payment cuts. Finally, Medicaid has generally been understudied by researchers, and this study can add to the very limited literature on hospital response to changes in Medicaid payments. While the study includes a large number of patients, the number of hospitals included was fairly limited. In order to maintain strong internal validity, hospitals that mechanically would not have seen a large impact of the Medicaid fee decrease were excluded from the study. Given the lack of significant changes to access to care or intensity of care among Medicaid patients, it was essential to focus on hospitals likely to see large impacts of the payment decrease. It is also important to note that this study focused on a relatively short-term response (i.e., within five quarters),[22] and it could be that the major response to payment reductions occurs in the long term. Some research has shown that at least in the short term, hospitals do not have strong treatment-related responses to

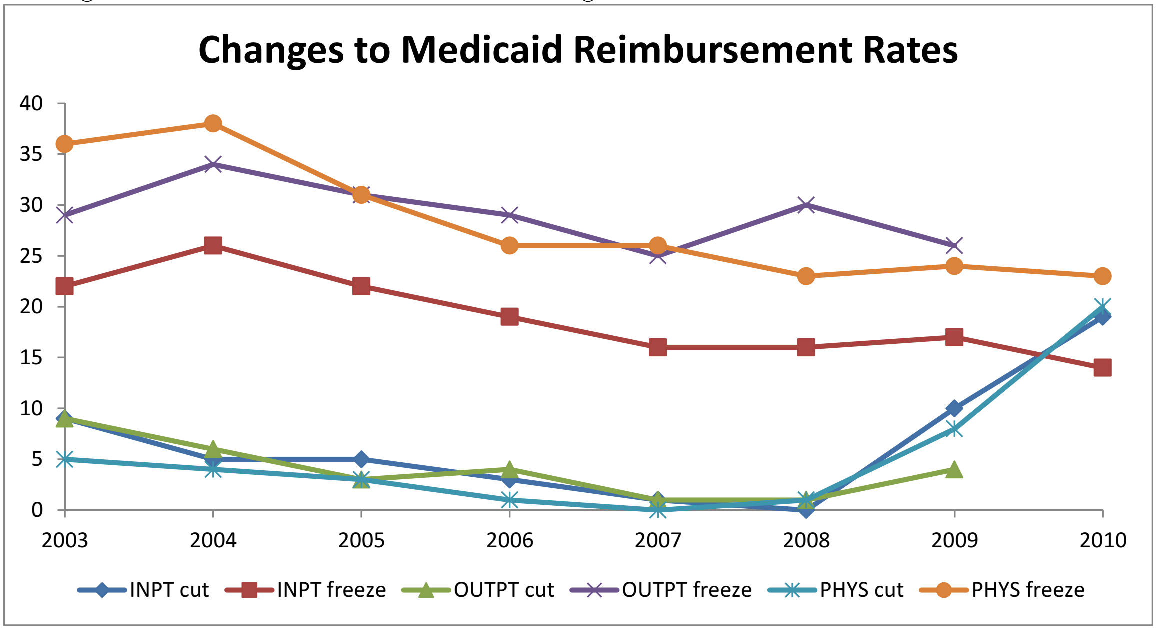
[22] The length of the study period was chosen to avoid confounding with changes to the policy that occurred in late 2009.

reimbursement incentives (US GAO, 2015).

The major contribution of this research to the literature is to shed light on the way hospitals respond to Medicaid payment decreases along patient care margins. Prior to this work, very little research had addressed this issue. A number of papers have studied hospital response to Medicare payment changes, or else physician response to Medicaid payment changes, but prior work that has explicitly addressed hospital response to Medicaid payment cuts is extremely limited. The challenges faced by researchers in understanding the institutional details of Medicaid programs, and the inherent issues with national generalizability have led to a general dearth of research on the Medicaid program. Despite its limitations, this study provides valuable insight into how hospitals may respond to Medicaid payment cuts.

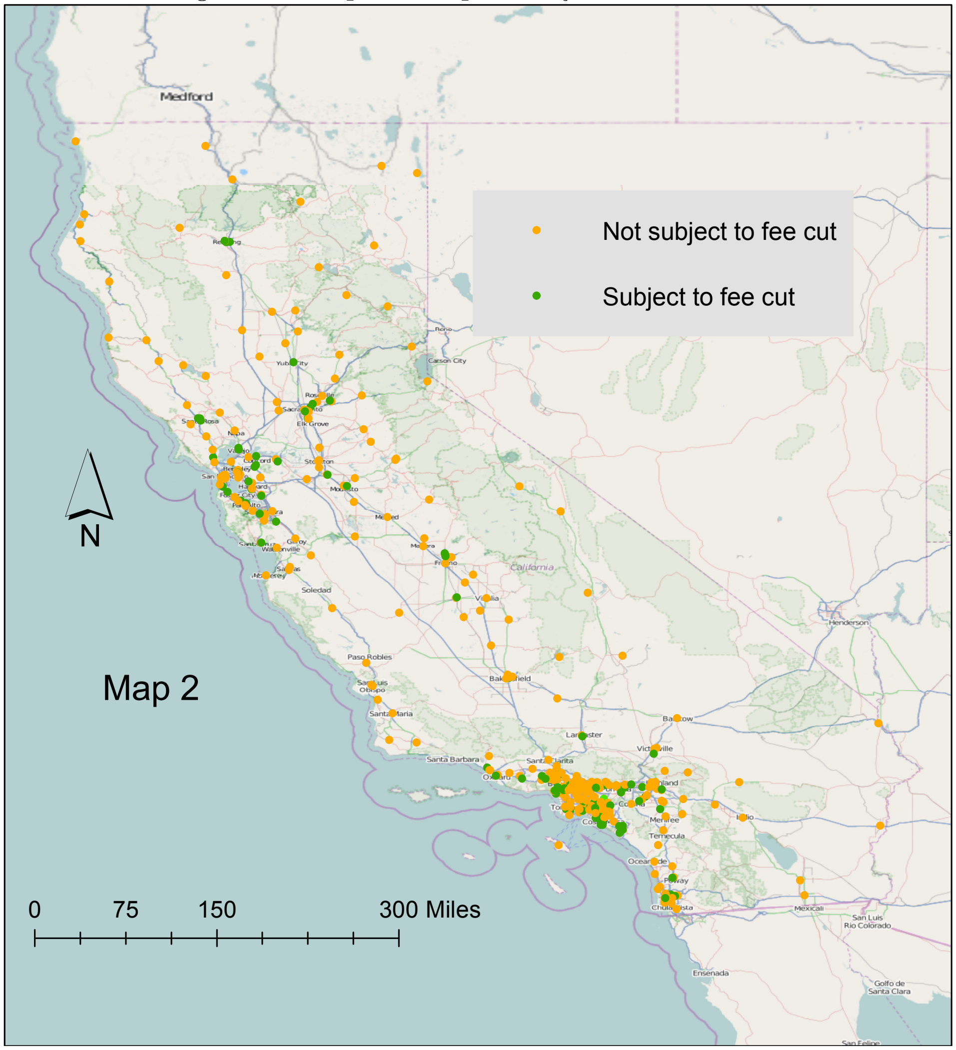
3.6. Tables & Figures

Figure 1: Number of States with Changes to Medicaid Reimbursement Rates



Note: Figure denotes the number of states in a year to enact the given change to reimbursement rates. Over time, the number of states enacting Medicaid reimbursement freezes decreases while the number of states using the more extreme alternative, reimbursement cuts, increases.

Figure 2: Map of Hospitals by Fee Cut Status



Note: Figure includes all hospitals subject to Medi-Cal fee decrease in 2008, including hospitals in closed HFPAs.

Figure 3: Sample Selection Flowchart

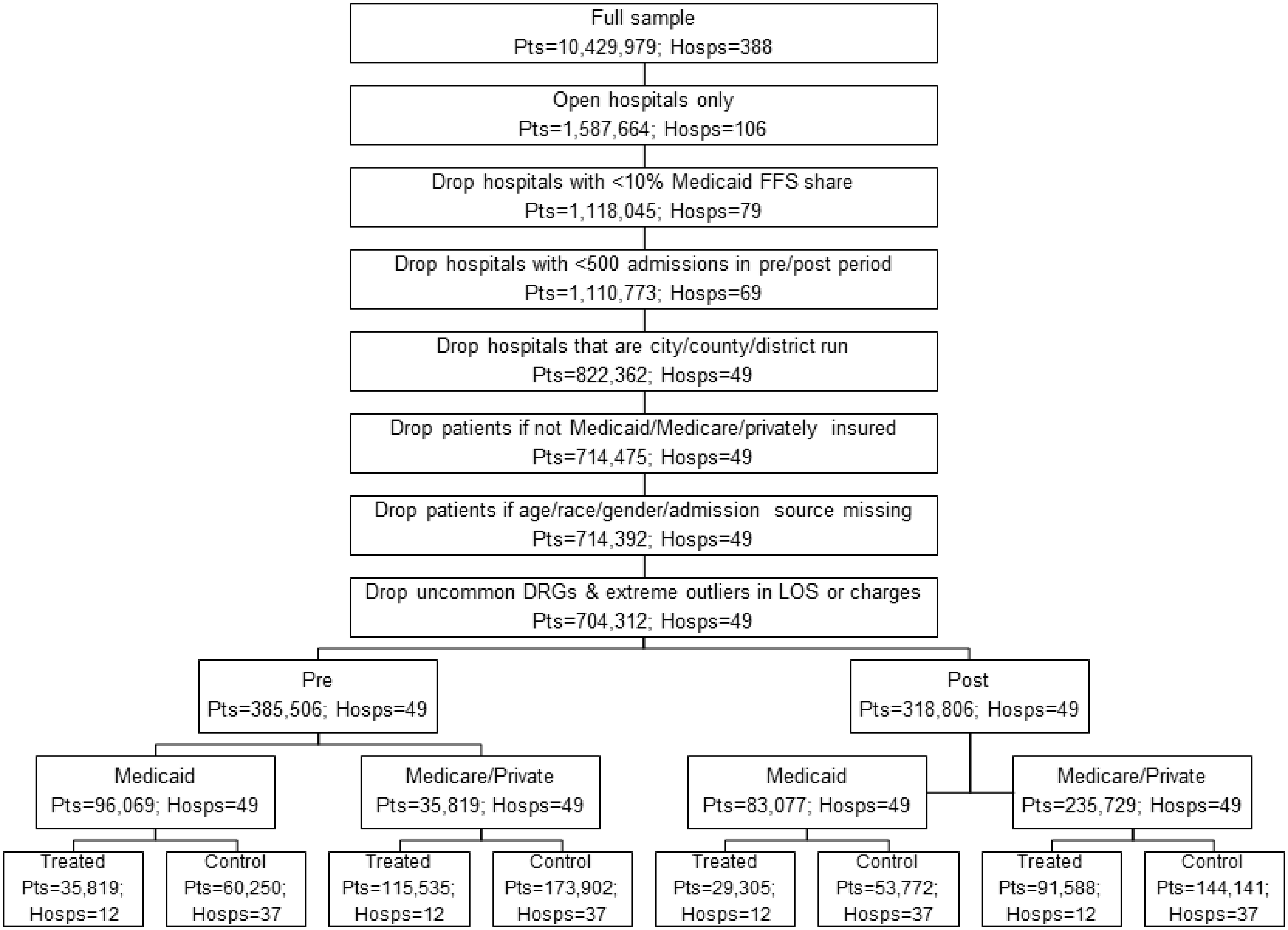


Table 3: Hospital Characteristics (2007)

	Treatment	Control
N*	12	37
Average Total Discharges	9,073	4,262
Average Medi-Cal Discharges	1,660	788
Average Total Hospital Days	41,488	19,237
Average Medi-Cal Days	7,762	4,104
Average Percentage Medi-Cal FFS	24.24%	24.32%

Note: Characteristics of hospitals included in the analyses (see sample selection flowchart in Table 3).

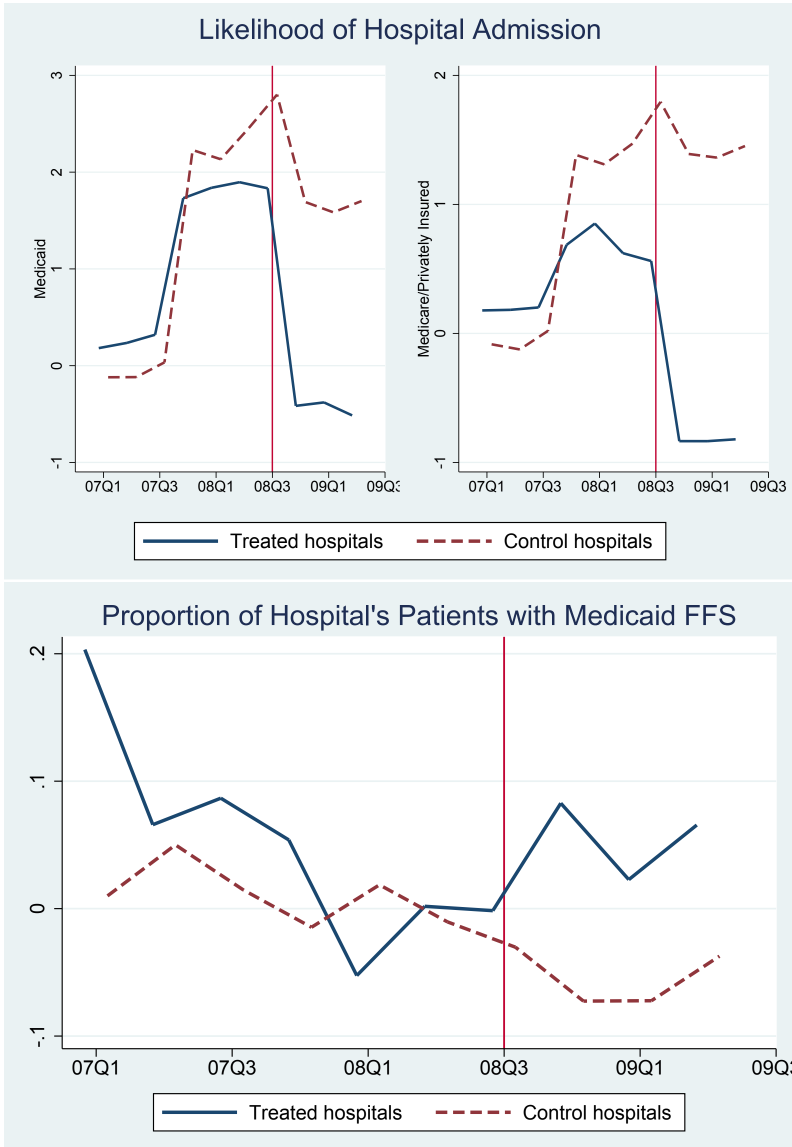
Table 4: Patient Characteristics

	Medicaid				Medicare/Privately Insured			
	In Treated Hospital		In Control Hospital		In Treated Hospital		In Control Hospital	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post
N	35,819	29,305	60,572	54,060	115,535	91,588	173,989	144,287
Age (mean)	24.00	24.08	23.13	23.66	55.23	55.00	58.57	58.44
Gender (percentage female)	67.70	67.91	69.38	68.90	57.38	57.37	58.65	58.86
Race (percentage)								
White	60.40	59.17	78.23	75.78	79.50	78.39	90.49	89.00
Black	5.84	5.99	3.64	3.72	2.84	2.88	2.38	2.61
Native American	1.21	1.14	1.95	2.28	0.50	0.48	0.85	1.01
Asian/Pacific Islander	6.43	6.30	2.22	2.34	10.64	10.92	1.52	1.49
Other	25.36	26.80	12.72	14.62	5.81	6.75	4.16	5.21
Unknown	0.76	0.60	1.24	1.26	0.71	0.58	0.60	0.69
LOS (mean, in days)	4.20	4.02	3.03	2.96	4.43	4.21	4.08	3.93
Charges (mean)	$50,815	$50,701	$19,292	$21,630	47,831	$50,727	$36,189	$39,745
Number of Procedures (mean)	1.24	1.25	1.31	1.30	1.80	1.76	1.49	1.44

Birth Cohort: N	9,790	7,799	18,183	15,511	9,823	7,679	13,647	10,978
Received c-section (vs. vaginal delivery) (percentage)	29.93	31.43	29.15	29.52	32.90	35.00	29.44	29.20

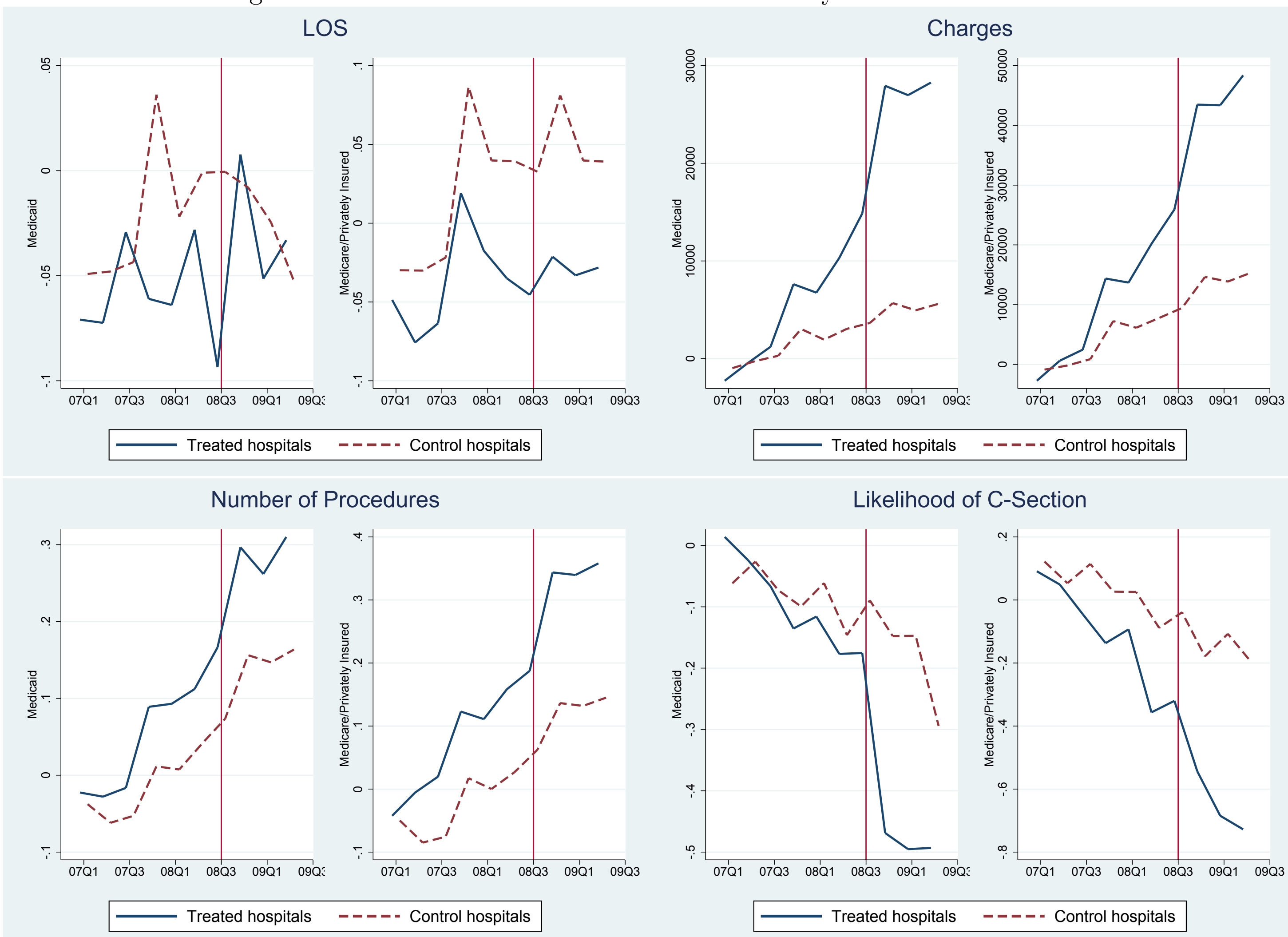
ED Patients: N	121,509	111,166	267,961	251,188	123,577	90,061	368,775	317,480
Admitted to hospital (percentage)	6.16	5.91	6.46	6.48	26.37	28.32	20.18	20.46

Figure 4: Difference-in-Differences Plots: Access to Care Measures



Note: Figures are plotted quarterly regression coefficients.

Figure 5: Difference-in-Differences Plots: Intensity of Care Measures



Note: Figures are plotted quarterly regression coefficients.

Measures of Access to Care

Note: In all regression analyses $Post \times Fee\,Cut$ is the coefficient of interest.

Table 5: Likelihood of Admission

	Medicaid		Medicare/Private	
	OR	SE	OR	SE
Admitted to Hospital				
Fee Cut	1.756	(0.574)	2.026**	(0.504)
Post	2.455**	(0.696)	1.720**	(0.328)
Post X Fee Cut	0.996	(0.104)	1.013	(0.105)
Male	1	(.)	1	(.)
Female	0.980	(0.0387)	0.926***	(0.0179)
White	1	(.)	1	(.)
Black	1.015	(0.136)	0.957	(0.115)
Native American/Eskimo/Aleut	0.966	(0.0918)	0.881	(0.138)
Asian/Pacific Islander	0.977	(0.122)	0.844	(0.0970)
Other	0.494*	(0.161)	0.486*	(0.163)
Unknown	0.728	(0.219)	0.754	(0.208)
Investor	1	(.)	1	(.)
Non Profit	1.222	(0.394)	1.113	(0.311)
County Medicaid FFS Proportion	0.244	(0.286)	0.729	(0.697)
County Unemployment	0.890*	(0.0478)	0.947	(0.0333)
County Average Income	1.000	(0.0000211)	1.000	(0.0000186)
Observations	740363		899790	

Exponentiated coefficients; Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Standard errors are clustered at the hospital level

OR - "Odds Ratio," SE - "Standard Error"

Table 6: Likelihood of Admission by ED Visit Severity

	ED Not Needed				ED Needed			
	Medicaid		Medicare/Private		Medicaid		Medicare/Private	
	OR	SE	OR	SE	OR	SE	OR	SE
Admitted to Hospital								
Fee Cut	1.766	(0.648)	1.874*	(0.561)	1.691	(0.603)	1.810*	(0.529)
Post	2.411*	(0.829)	1.681*	(0.394)	2.248*	(0.717)	1.585*	(0.343)
Post X Fee Cut	1.092	(0.117)	1.090	(0.130)	1.090	(0.124)	1.092	(0.114)
Male	1	(.)	1	(.)	1	(.)	1	(.)
Female	1.019	(0.0592)	0.908***	(0.0228)	1.000	(0.0444)	0.923***	(0.0194)
White	1	(.)	1	(.)	1	(.)	1	(.)
Black	1.073	(0.157)	0.990	(0.127)	1.114	(0.173)	0.990	(0.123)
Native American/Eskimo/Aleut	0.996	(0.129)	0.851	(0.137)	0.997	(0.130)	0.832	(0.140)
Asian/Pacific Islander	0.679**	(0.0866)	0.771	(0.104)	0.769	(0.109)	0.794	(0.102)
Other	0.468*	(0.153)	0.471*	(0.158)	0.464*	(0.155)	0.475*	(0.162)
Unknown	0.616	(0.196)	0.745	(0.204)	0.618	(0.197)	0.743	(0.199)
Investor	1	(.)	1	(.)	1	(.)	1	(.)
Non Profit	1.226	(0.422)	1.037	(0.336)	1.164	(0.407)	1.014	(0.330)
County Medicaid FFS Proportion	0.248	(0.337)	0.656	(0.705)	0.229	(0.298)	0.654	(0.695)
County Unemployment	0.896	(0.0567)	0.952	(0.0403)	0.903	(0.0533)	0.961	(0.0383)
County Average Income	1.000	(0.0000225)	1.000	(0.0000208)	1.000	(0.0000217)	1.000	(0.0000199)
Observations	456939		473703		409709		477053	

Exponentiated coefficients; Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Standard errors are clustered at the hospital level

OR - "Odds Ratio," SE - "Standard Error"

Table 7: Hospital Mix

	Proportion of Patients with Medicaid FFS	
Fee Cut	-0.0209	(0.0173)
Post	-0.00262	(0.0107)
Post X Fee Cut	-0.0123	(0.0278)
Investor	0	(.)
Non Profit	-0.0913***	(0.0166)
County Medicaid FFS Proportion	0.272***	(0.0386)
County Unemployment	0.00331	(0.00200)
County Average Income	0.00000264***	(0.000000629)
Constant	0.0757	(0.0424)
Observations	539	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Outcome is at the hospital level, measured as the proportion of Medicaid FFS patients in the hospital in the overall population of patients with Medicaid, Medicare, or private insurance.

Measures of Intensity of Care

Table 8: Length of Stay

	Medicaid		Medicare/Private	
Length of Stay				
Fee Cut	0.110***	(0.0265)	0.0678*	(0.0324)
Post	0.0110	(0.0179)	0.0244	(0.0210)
Post X Fee Cut	0.000166	(0.0182)	-0.00118	(0.0175)
Male	0	(.)	0	(.)
Female	-0.0514*	(0.0229)	0.0118	(0.00685)
White	0	(.)	0	(.)
Black	0.0951**	(0.0307)	0.102***	(0.0212)
Native American/Eskimo/Aleut	0.0296	(0.0326)	-0.0158	(0.0172)
Asian/Pacific Islander	0.113***	(0.0338)	0.136***	(0.0284)
Other	-0.0271	(0.0268)	0.0444	(0.0263)
Unknown	-0.0368	(0.0301)	0.0282	(0.0272)
Investor	0	(.)	0	(.)
Non Profit	0.0641	(0.0593)	0.0332	(0.0619)
County Medicaid FFS Proportion	-0.0368	(0.130)	0.0472	(0.202)
County Unemployment	-0.00475	(0.00452)	-0.00354	(0.00505)
County Average Income	0.00000200	(0.00000210)	0.00000124	(0.00000281)
Observations	175903		525399	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Standard errors are clustered at the hospital level

Table 9: Charges

	Medicaid		Medicare/Private	
Fee Cut	2755.9	(2127.9)	2460.5	(3363.1)
Post	2670.7**	(860.0)	6517.2**	(1903.8)
Post X Fee Cut	-619.3	(1025.0)	-232.5	(1460.3)
Male	0	(.)	0	(.)
Female	-1277.6**	(401.9)	-1164.0***	(258.7)
White	0	(.)	0	(.)
Black	-184.3	(1223.0)	-171.7	(1391.7)
Native American/Eskimo/Aleut	-1514.1	(1040.8)	-1486.3	(1488.9)
Asian/Pacific Islander	-601.2	(1806.0)	-1251.6	(3199.0)
Other	-535.3	(1280.7)	-950.0	(2032.0)
Unknown	-889.8	(890.3)	1180.1	(1606.9)
Investor	0	(.)	0	(.)
Non Profit	257.4	(2743.2)	-5004.8	(5478.1)
County Medicaid FFS Proportion	8317.1	(6702.4)	15346.3	(13198.0)
County Unemployment	-151.8	(209.1)	-508.1	(460.9)
County Average Income	0.161	(0.122)	0.290	(0.204)
Observations	175903		525399	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Standard errors are clustered at the hospital level

Table 10: Number of Procedures

	Medicaid		Medicare/Private	
Number of Procedures				
Fee Cut	-0.0104	(0.0703)	0.0152	(0.0564)
Post	0.0543	(0.0373)	0.0632*	(0.0306)
Post X Fee Cut	0.00459	(0.0415)	0.0286	(0.0380)
Male	0	(.)	0	(.)
Female	-0.0493**	(0.0166)	-0.0388***	(0.00731)
White	0	(.)	0	(.)
Black	-0.0660	(0.0359)	-0.0188	(0.0297)
Native American/Eskimo/Aleut	0.00706	(0.0310)	0.0984*	(0.0393)
Asian/Pacific Islander	0.129*	(0.0641)	0.125**	(0.0409)
Other	-0.0376	(0.0524)	-0.0249	(0.0336)
Unknown	-0.0474	(0.0459)	0.0390	(0.0351)
Investor	0	(.)	0	(.)
Non Profit	-0.0913	(0.112)	-0.0487	(0.0642)
County Medicaid FFS Proportion	0.157	(0.225)	0.302	(0.207)
County Unemployment	-0.00961	(0.0100)	-0.0186	(0.00973)
County Average Income	3.78e-08	(0.00000361)	-0.000000378	(0.00000258)
Observations	175903		525399	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Standard errors are clustered at the hospital level

Table 11: Likelihood of C-Section Among Birth Cohort

	Medicaid		Privately Insured	
	Odds Ratio	Std. Error	Odds Ratio	Std. Error
csection				
Fee Cut	0.977	(0.148)	0.981	(0.0996)
Post	0.879	(0.0705)	0.856*	(0.0625)
Post X Fee Cut	1.054	(0.0569)	1.125**	(0.0473)
White	1	(0)	1	(0)
Black	1.154*	(0.0731)	1.214*	(0.106)
Native American/Eskimo/Aleut	0.982	(0.0948)	1.409***	(0.140)
Asian/Pacific Islander	0.586***	(0.0543)	0.787	(0.0971)
Other	0.882	(0.0632)	1.159	(0.107)
Unknown	0.974	(0.115)	1.062	(0.131)
Observations	51283		42127	

Exponentiated coefficients; Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Standard errors are clustered at the hospital level

Results from Matched Analysis

Figure 6: Hospitals' Propensity to Be Subject to Payment Cut (Distributions)

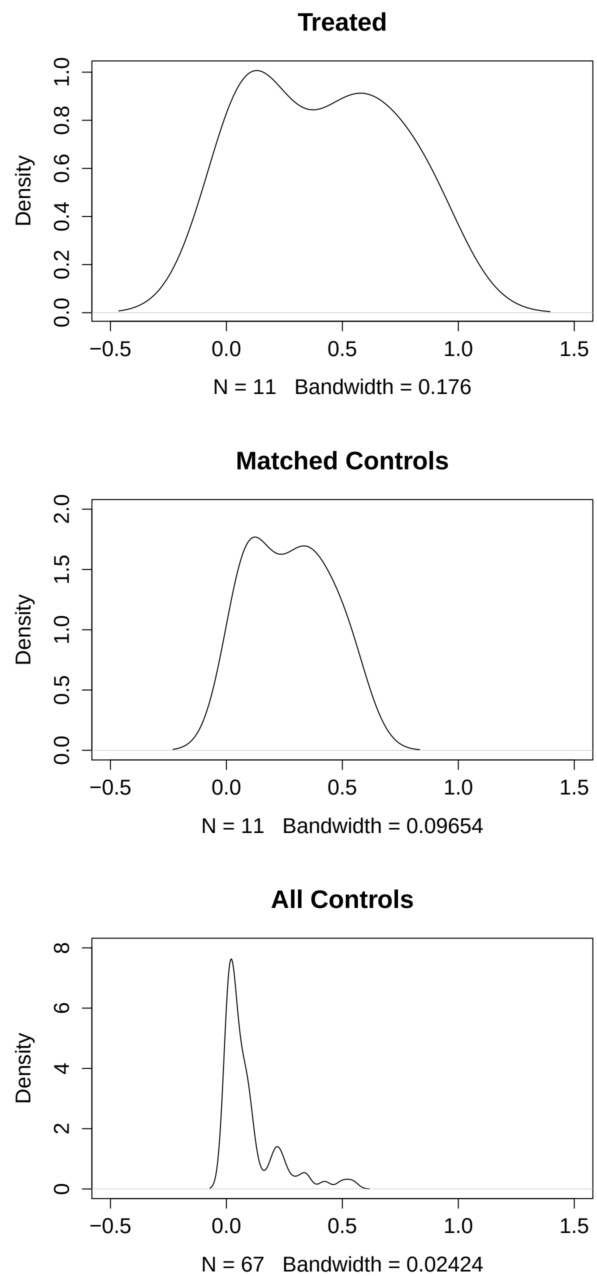


Table 12: Standardized Differences Among Hospitals Before and After Matching

	Standardized Differences Before	Standardized Differences After
Total Discharges	1.202	0.178
Average Available Beds	1.049	0.299
Proportion of Medicaid FFS Patients	0.037	0.222
County Level Unemployment Rate	-0.747	-0.125
County Level Average Income	0.807	0.219
County Level Medicaid FFS Enrollment (Proportion)	-0.373	-0.036

Note: Generally, standardized differences of less than 0.2 imply acceptable covariate balance. The matching procedure successfully reduces standardized diffences between treated and control hospitals to below 0.2 for most characteristics, and in other cases is an improvement over the unmatched differences.

Table 13: Likelihood of Admission

	Primary Effect		Spillover Effect	
	Odds Ratio	Std. Error	Odds Ratio	Std. Error
Hospital Admission				
Fee Cut	0.772***	(0.0213)	1.040**	(0.0144)
Post	0.833***	(0.0218)	0.966**	(0.0127)
Post X Feecut	1.193***	(0.0449)	1.054**	(0.0198)
Observations	223080		394304	

Exponentiated coefficients; Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Standard errors are clustered at the hospital level

Table 14: Length of Stay

	Medicaid		Medicare/Private	
LOS				
Fee Cut	0.112***	(0.0153)	0.0425***	(0.00643)
Post	-0.0182	(0.0138)	0.0161**	(0.00611)
Post X Feecut	0.000960	(0.0197)	-0.0127	(0.00864)
Observations	46700		184544	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 15: Charges

	Medicaid		Medicare/Private	
Fee Cut	1675.4***	(348.5)	7472.6***	(265.6)
Post	1589.0***	(285.9)	5088.6***	(242.1)
Post X Feecut	-134.9	(425.5)	107.6	(357.1)
Observations	46700		184544	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 16: Number of Procedures

	Primary Effect		Spillover Effect	
Number of Procedures				
Fee Cut	0.0460***	(0.0104)	0.0564***	(0.00594)
Post	0.0488***	(0.00933)	0.0207***	(0.00572)
Post X Feecut	0.0229	(0.0126)	0.0177*	(0.00796)
Observations	46700		184544	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 17: Likelihood of C-Section Among Birth Cohort

	Medicaid		Private	
	Odds Ratio	Std. Error	Odds Ratio	Std. Error
C-Section				
Fee Cut	1.159**	(0.0535)	1.102*	(0.0450)
Post	1.030	(0.0477)	1.046	(0.0428)
Post X Feecut	0.966	(0.0625)	1.044	(0.0593)
Observations	18448		22668	

Exponentiated coefficients; Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

CHAPTER 4 : The Effect of Medicaid Payment Incentives on Patient Care in California Hospitals

4.1. Introduction

Insurance providers may make use of a variety of financial incentives in order to encourage both health care providers and consumers to take costs into consideration when making decisions. For state Medicaid programs, where demand-side incentives are less common, changing incentives to health care providers is becoming increasingly common. One of the most commonly used reimbursement-based incentives in hospital payments has been the use of DRG-based prospective payments. Medicare, as well as a number of state Medicaid programs, switched their hospital reimbursement systems from fee-for-service based systems to DRG-based systems in the 1980s, with the basic concept being that a DRG-based payment system shifted some of the risk onto the provider (rather than on the insurer alone), and gave providers incentives to lower costs.

This chapter studies how hospitals may respond to a shift in reimbursement methodology to a prospective, DRG-based payment system. I study California Medicaid's 2013 shift to DRG-based payments. Prior to this shift, some hospitals were paid on a fee-for-service basis, while others were paid on a per-diem basis. The shift to a DRG-based payment system represents a change in incentives for hospitals. Ex ante, I expect the strongest effects to occur where there is a clear reversal in incentive from the prior payment method.

I use a comprehensive hospital and emergency department discharge data set for the years 2012-2014 from the California Office of Statewide Health Planning and Development (OSHPD). Using a difference-in-differences approach, I measure the impact of the 2013 shift to DRG-based payments by Medicaid on access to care, intensity of care, and complications of care for Medicaid patients. For identification, I take advantage of the fact that the new payment system was implemented six months earlier in private hospitals than in public hospitals. To test for spillover effects onto non-Medicaid patients, I also evaluate the impact of the introduction of Medicaid DRG payments on access to care, treatment intensity, and complications of care for Medicare, privately insured, and uninsured patients. To address concerns that treated and control hospitals may be different from one another, I conduct sensitivity analyses of the same outcomes among private hospitals only, using the lagged Medicaid proportion of hospitalized patients at the county level for identification. These analyses provide a number of insights into hospitals' responses to changes in Medicaid payment methodology.

I find that the major response of hospitals to the implementation of DRG payments is a reduction in the average inpatient length of stay. Furthermore, this reduction is driven primarily by hospitals previously reimbursed on a per diem basis. This implies that hospitals respond strongly to clear changes in incentives. Paid on a per diem basis, hospitals have an incentive to increase LOS; this incentive is reversed under a DRG payment system. There are no significant changes in treatment or access to care for non-Medicaid patients. Medicaid policymakers should take note that hospitals still respond to strong incentives; despite California having relatively low LOS on average compared to the rest of the country, hospitals reduced LOS in response to DRG payments.

4.2. Empirical Approach

4.2.1. Outcome Measures

1. **Access to care** is measured in two ways:

    (a) First, the *likelihood of admission* is defined as the likelihood of inpatient admission to the hospital following a visit to the same hospital's emergency department.

    (b) Second, *hospital-level insurance mix* is defined at the hospital level as the proportion of Medicaid FFS patients divided by the total population of patients.

2. **Intensity of care** is measured in a number of ways:

    (a) First, it is measured as the *length of stay (LOS)*, which is included in each hospital discharge record.

    (b) Second, it is measured as the *total charges associated with the discharge*, with the assumption that higher charges generally imply more intense care.

    (c) A third measure of intensity of care is measured as the *number of procedures* associated with the discharge (under the assumption that a greater number of procedures generally implies more intense care).

    (d) Finally, I also conduct analyses among a subset of patients for whom defining intensity of care is much more straightforward—women admitted to the hospital for childbirth. Childbirth is an ideal setting to study intensity of care, since there are essentially only two options for care (vaginal delivery or delivery via cesarean section), and one (and only one) of those is associated with every delivery. Furthermore, childbirth is commonly used in the literature to study intensity of care because as previous work has noted, the underlying costs in terms of physician time are considered similar between cesarean section and vaginal delivery, but cesarean section is typically reimbursed at a higher rate (Gruber et al., 1999). Finally, childbirth is particularly useful to study in the context of this paper since it is a very common reason for hospital admissions among the Medicaid population. Therefore, among the cohort of women admitted to the hospital for childbirth, I also measure the *likelihood of receiving a cesarean section*.

3. **Complications of care** may be coded for two reasons: actual complications occurring; or, an administrative response by hospitals known as "upcoding," whereby hospitals may code patients as being more "severe" in order to extract higher DRG payments (Dafny, 2005). While I cannot distinguish between those two possibilities in the data, an increase in complications of care among Medicaid patients could imply either poorer quality of care, or an upcoding response. Therefore, among the cohort of women admitted to the hospital for childbirth, I examine the proportion of patients coded as having births "with complications" versus "without complications."

4.2.2. Identification Strategy

To identify the effects of the shift to DRG-based payments, I include in my sample all private and non-designated public hospitals in California, as these hospitals all became subject to DRG-based payments by Medicaid either on July 1, 2013, or on January 1, 2014. The basic identification strategy is based on the staggered implementation of the DRG payment methodology; private hospitals were switched to DRG payments in July 2013, while NDP hospitals were switched in January 2014. This provides a sixmonth study period (July 2013 to December 2013) during which I compare outcomes among private hospitals (the treated group) to outcomes among NDP hospitals (the control group).

To address concerns that private and NDP hospitals may differ on unobservable characteristics, as a sensitivity analysis, I also conduct all analyses among private hospitals only. However, this presents an issue, as the source of identification from the primary analyses is no longer available. Therefore, I instead use the proportion of hospitalized patients covered by Medicaid FFS in 2012 at the county level to provide variation. In these analyses, I make the assumption that hospitals in counties with a smaller proportion of Medicaid FFS patients should have a smaller response to the implementation of DRG payments.

4.2.3. Sample Selection

A sample selection flowchart is provided in Figure 7. The sample of hospitals was limited to private or NDP hospitals only, with private hospitals making up the treated group and NDP hospitals making up the controls. In addition, I exclude hospitals from the sample that were previously non-contract hospitals in closed HFPAs. These hospitals are excluded because prior to the switch to DRG-based payments, they were by definition treating only very small numbers of Medicaid FFS patients. This restriction was no longer in places once DRG payments were introduced, so I exclude these hospitals because I cannot separately identify the effect of DRG payments versus the effect of the removal on the restriction of the treament of Medicaid FFS patients.

In addition, to ensure that the hospitals in the study are sufficiently exposed to the policy change, I limit the sample of hospitals to those with at least a ten percent share of Medicaid FFS patients in the pre-period.[23] Additionally, I drop hospitals with fewer than 500 admissions in either the pre- or post-periods, and hospitals that were run by a city, county, or district.[24] One concern with these analyses is the issue of how to handle Medicaid managed care plans, which a number of counties in California mandate for subsets of their Medicaid population. To address this issue, I exclude from my sample of hospitals any hospital in a county with *changes* to its offerings of managed care plans or requirements during the study period. Differences between counties that remained consistent throughout the study period are controlled for in the difference-in-differences setup. This resulted in a final sample of 122 treated hospitals and 12 control hospitals. For sample selection of patients, only patients insured by Medicaid FFS, Medicare, or private insurance were included in the sample. Patients for whom certain variables (age, race, or gender) were missing were excluded from the analysis. Finally, patients with very uncommon conditions or who were extreme outliers in LOS or charges were excluded from analysis as well, leading to a final sample of 2,130,768 patients.

One concern with the analyses studying the likelihood of hospital admission for patients appearing in the ED, is that it may be unlikely to see a response across all reasons for ED visit. For example, in the case of an immediate life-threatening emergency, it is unlikely (and illegal) for hospitals to refuse to treat a patient based on insurance status (CMS, 2012). Therefore, in addition to looking at overall ED visits, I also examine ED visits broken down into visits considered to require emergency care, versus those that are primary care treatable or non-emergent, using an ED classification algorithm developed by researchers at New York University (Billings et al., 2000). The algorithm provides a percentage of cases for a given diagnosis that are

[23] Sensitivity analyses around this cutoff were conducted, and did not change the results of the study.

[24] These hospitals were dropped because they only appeared among the control group.

considered *non-emergent* (ED care not needed), *emergent but primary care treatable* (ED care not needed), *emergent but preventable* (ED care needed), and *emergent and not preventable* (ED care needed). I break up the sample into ED visits with a non-zero proportion of "ED care not needed" versus those with a non-zero proportion of "ED care needed."[25]

4.2.4. Difference-in-Differences Analysis

I utilize patient discharge data and emergency department data from quarter 1 of 2012 to quarter 4 of 2013. The change to DRG based payments took effect in July 2013 for private hospitals, and in January 2014 for NDP hospitals, so this provides six quarters of pre-data and two quarters of post-data. While the post period is relatively short, its length is necessary given the change in payment methodology for the control hospitals in January 2014. In addition, given the major change in reimbursement methodology, I expect that changes in outcomes may occur very quickly following the policy change.

I use a difference-in-differences approach to compare outcomes in hospitals that were subject to DRG payments versus those that were not, prior to and following its July 2013 implementation. The regression is specified as follows:

$$\begin{aligned} Y_{ijtk} = \beta_0 + \beta_1 \cdot Post_t + \beta_2 \cdot Treated_j + \beta_3 \left(Post \times Treated\right)_{tj} + \\ \beta_4 \cdot \mathbf{X_i} + \beta_5 \cdot \mathbf{Z_j} + \beta_6 \cdot \mathbf{W_k} + \varepsilon \end{aligned} \tag{4.1}$$

where Y is the outcome of interest. *Post* indicates the admission occurred at time

[25] These are not mutually exclusive categories. However, this is the broadest way to classify the data without introducing arbitrary cutoff points.

t following DRG implementation, $Treated$ indicates that hospital j was subject to DRG payments in July 2013, and $Post \times Treated$ is the interaction of the two. $\mathbf{X}$ is a vector of patient-level covariates for patient i, $\mathbf{Z}$ is a vector of hospital level covariates, and $\mathbf{W}$ is a vector of county-level covariates for county k. Patient level demographics include age, gender, ethnicity (Hispanic or non-Hispanic), and race. Additionally, patient health characteristics associated with the admission are included. Hospital level covariates include the profit status of the hospital (for profit vs. not-for-profit), the 2012 Medicaid FFS proportion of patients, and the hospital's prior status as a contract or non-contract hospital. County level characteristics include the unemployment rate and average income levels, as well as a county-level fixed effect. For continuous outcomes (i.e., charges), the equation is estimated via linear regression. For count outcomes (i.e., length of stay, number of procedures), the equation is estimated using Poisson regression. Finally, to estimate event likelihood (i.e., likelihood of admission, likelihood of c-section), I use logistic regression. The analyses are done separately for Medicaid fee-for-service patients (primary effect), and then for Medicare or privately insured patients to test for secondary effects. Standard errors are cluster robust, with clusters defined at the hospital level (Bertrand et al., 2004).

I further break down all Medicaid patient-level regressions by the previous payment methodology of the hospital. That is, I separately run the Medicaid patient regressions among previous contract hospitals (that were paid on a per diem basis) and previous non-contract hospitals (that were paid on a fee-for-service basis), to understand if the effects (if any) differ by previous payment method. In these regressions, the control for the hospital's prior contracting status is therefore dropped.

To understand the impact of the fee cut on the hospital-level mix of patients by insurer type, I estimate the following equation:

$$Y_{jtk} = \beta_0 + \beta_1 \cdot Post_t + \beta_2 \cdot Treated_j + \beta_3 \left(Post \times Treated\right)_{tj} + \beta_4 \cdot \mathbf{Z_j} + \beta_5 \cdot \mathbf{W_k} + \varepsilon \quad (4.2)$$

where the outcome Y is the proportion of Medi-Cal FFS patients, defined at the hospital level. Since discharges are on the quarter-year level, each hospital has one observation per quarter-year. I use heteroskedasticity robust standard errors.

4.2.5. Sensitivity Analyses

One issue that may be raised with a difference-in-differences strategy is that it may suffer from bias if private hospitals differ in unobservable ways from NDP hospitals, which is the source of identification in the main analysis. Therefore, as a sensitivity analysis, I also conduct these analyses among the subset of private hospitals only. In this case, a new identification strategy is required. I make use of the lagged county-level proportion of hospitalized patients covered by Medicaid FFS. I make the assumption here that hospitals in counties with a larger proportion of Medicaid FFS patients will have a stronger response to the change in payment methodology.

In these analyses, I use slightly different inclusion criteria for the sample of hospitals. I no longer exclude hospitals based on their proportion of Medicaid FFS patients, given that this is part of the identification strategy. In addition, I no longer exclude 2014 admissions. I exclude 2014 admissions in the main analysis because the control group of hospitals gets switched over to DRG payments in January 2014. However, this is not an issue in these sensitivity analyses. The final sample in this approach consists of 152 hospitals and 4,790,111 patients.

I analyze the same outcomes as in the main analyses, but rather than a "true" difference-in-differences set up, I use the continuous 2012 county-level Medicaid FFS proportion rather than a binary "treated" variable, as follows:

$$Y_{ijtk} = \beta_0 + \beta_1 \cdot Post_t + \beta_2 \cdot MdcdProp_j + \beta_3 \left(Post \times MdcdProp\right)_{tj} + \beta_4 \cdot \mathbf{X_i} + \beta_5 \cdot \mathbf{Z_j} + \beta_6 \cdot \mathbf{W_k} + \varepsilon \quad (4.3)$$

Here $\mathbf{X_i}$ are the patient-level characteristics, $\mathbf{Z_j}$ are the county-level characteristics, and $\mathbf{W}_k$ are the county-level variables, as in the main analysis, with the only difference being that there is no longer a county fixed effect, given that the 2012 Medicaid porportion is measured at the county-level and is time-invariant.

4.3. Data Sources

I use discharge-level, hospital-level, and county-level data. The discharge data includes information on patients discharged from both hospitals and emergency departments (EDs), and includes patient characteristics as well as diagnosis and treatment variables. Hospital-level variables include both general hospital characteristics, as well as information regarding the timing of the hospital's DRG payment implementation and information regarding the prior payment methodology. Finally, county-level variables include variables on county-level unemployment, income levels, and the proportion of hospitalizations covered by Medicaid FFS. The sources for each of these are described in more detail in the following subsections.

4.3.1. Patient-Level Variables

Patient Discharge Data

Patient-level discharge data come from the California Office of Statewide Health Planning and Development (OSHPD) for the years 2012 to 2014. I use the non-public use versions of the inpatient discharge data and the emergency department data to ensure full access to demographic variables. The inpatient discharge data include a record for every inpatient discharge from a California-licensed hospital. Each record consists of the hospital at which care was received, date of birth, gender, ethnicity, race, principal language spoken, county of residence, zip code, admission date, discharge date, length of stay, source of admission (own hospital ED, other hospital ED, no ED), disposition, expected source of payment (Medicare, Medi-Cal, private coverage, etc), type of coverage (traditional FFS, managed care, etc), total charges, major diagnostic category (MDC), Medicare Severity Diagnosis Related Group (MS-DRG), principal diagnosis, other diagnoses, principal procedure, and other procedures. I control for diagnoses by using the MS-DRG grouping.

Emergency Department Data

Patient-level emergency department data for the years 2012 to 2014 also come from OSHPD. The ED data include a record for every ED encounter that involved face-to-face contact with a provider at a hospital licensed to provide emergency medical services. Patients who left the ED without being seen are not included in the data. The ED data include variables on the facility at which emergency care was sought, the patient's date of birth, gender, ethnicity, race, principal language spoken, county of residence, zip code, service date, disposition, expected source of payment, principal and other diagnoses, and principal and other procedures. Since DRGs are not included in the ED data, I use the Clinical Classifications Software, a diagnosis-grouping algorithm, in order to cluster diagnoses into clinically meaningful categories (Elixhauser et al., 2014). It is also important to note that in analyses using the ED data only, I can only observe the payer category (Medicare, Medi-Cal, private coverage, etc.), but not the type of coverage (managed care vs. FFS). Therefore, I include all Medi-Cal patients in the analyses.

4.3.2. Hospital-Level Variables

Basic hospital-level variables were found in the OSHPD data. This includes a unique hospital identification number and hospital name, hospital zip code, hospital county, and the total number of discharges by year. Additional hospital-level variables are described below.

Information on the hospitals' status as private hospitals, designated public hospitals, or non-designated public hospitals (and therefore the timing and implementation of DRG payments) was available from a hospital characteristics file publicly available from the California Department of Health Care Services.[26] Information on the contracting status of each hospital, as well as the area status (open or closed) of the HFPA in which the hospital is found, was hand-collected from a number of sources. The HFPA to which each hospital was assigned was found in hospital financial reports that are publicly available from OSHPD.[27] HFPA area status (closed or open) was found in the California Medical Assistance Commission (CMAC) Annual Reports to the Legislature (2009-2010).[28] Finally, the contracting status of each hospital came from the CMAC reports and individual annual hospital financial disclosure reports publicly available from OSHPD.[29] This allowed for the identification of the prior payment methodology, and for the exclusion of hospitals that were previously non-contract hospitals in closed HFPAs.

[26] http://www.dhcs.ca.gov/provgovpart/Pages/DRG-pricing-sfy2013-14.aspx
[27] http://www.oshpd.ca.gov/hid/Products/Hospitals/QuatrlyFinanData/CmpleteData/default.asp
[28] http://www.dhcs.ca.gov/services/spcp/Pages/default.aspx
[29] https://siera.oshpd.ca.gov/FinancialDisclosure.aspx

4.3.3. County-Level Variables

County-level variables are included in regression analyses to control for any differential effects by geographic region, and include the proportion of hospitalization attributable to Medi-Cal fee-for-service, unemployment rates, and income levels. The proportion of Medi-Cal hospitalizations was calculated directly from the OSHPD data. County-level unemployment statistics come from the Bureau of Labor Statistics Local Area Unemployment Statistics.[30] These data include monthly county-level unemployment rates, and were merged into the OSHPD patient discharge data based on hospital county. Finally, county-level income levels come from the U.S. Census Bureau Small Area Income and Poverty Estimates.[31] These data include annual county-level income rates, and were merged into the OSHPD patient discharge data based on hospital county.

4.4. Results

4.4.1. Descriptive Statistics

Descriptive statistics of the hospitals included in the analysis are presented in Table 18. A total of 110 treated hospitals and 12 control hospitals met the inclusion criteria for the analysis. Treatment hospitals were on average fairly similar to control hospitals, both in terms of total discharges and total hospital days. They also served similar numbers of proportions of Medi-Cal FFS patients, with nearly a quarter of patients on average covered by Medi-Cal FFS.

Descriptive statistics of Medicaid FFS patients are presented in the left four columns of Table 19. Among the Medicaid FFS population, the average age is 21-24 years

[30] http://www.bls.gov/lau/data.htm
[31] http://www.census.gov/did/www/saipe/index.html

old and over two-thirds are female, with little variation between treatment/control hospitals or pre/post periods. About 60 percent of the Medicaid population is white, but control hospitals see a smaller proportion of black Medicaid patients than treatment hospitals (5% versus 8%). Length of stay increased in both treatment and control hospitals from the pre-period to the post-period. Similarly, average charges vary widely between treatment and control hospitals, but on average increase in both groups from the pre-period to the post-period. Within the cohort of women admitted to the hospital for childbirth, there is little change in the proportion of women receiving a cesarean section compared to vaginal birth; there is also little change in the proportion of women coded as having a birth with complications. Among patients appearing in the ED, there were slight reductions in the proportion admitted to the hospital among both treatment and control hospitals.

Descriptive statistics of Medicare and privately insured patients are presented in the right four columns of Table 19. These patients are on average older than Medicaid patients (due to the Medicare population), but there are no major changes in age over time. Almost 60% of patients in both treated and control hospitals are female, and similar to the Medicaid population, a higher proportion of patients in treated hospitals are black. In both treated and control hospitals, there is very little change in inpatient LOS, charges, or the average number of procedures per discharge. Among the cohort of women admitted to the hospital for childbirth, the proportion receiving a c-section as well as the proportion with complications remained stable over time in both treatment and control hospitals. Similarly, there was little change in the proportion of patients admitted to the hospital given a visit to the ED.

4.4.2. Access to Care

The plots in Figure 8 present the difference-in-differences plots of access to care measures. The top pair of plots shows the trends in likelihood of hospital admission over time among both Medicaid patients and Medicare/privately insured patients. Based on the plots alone, it appears that after the implementation of DRG payments by Medicaid, the likelihood of hospital admission given an ED visit shows relatively little change in treated hospitals, but increases in control hospitals. Table 21 presents the results of the difference-in-differences logistic regression on the likelihood of hospital admission.[32] The coefficient on $Post \times July1DRG$, presented as an odds ratio (OR), is the coefficient of interest. The results show that in response to the introduction of DRG payments by Medicaid, the likelihood of admission does not change significantly among Medicaid patients or among the Medicare and privately insured population. Even when the results for Medicaid patients are broken down by the hospital's previous payment methodology (Table 22), the effects remain small and not statistically significant. This suggests that it is unlikely that hospitals are systematically responding to the Medicaid payment change by changing their criteria for hospital admission from the ED.

To address concerns that not all ED visits may be responsive to changes in reimbursement, I also examine the results broken down by visits that were considered "ED Care Needed" versus visits that were considered "Primary Care Treatable" or "Non-Emergent." One might expect that there would be little response to payment changes among ED visits that are truly emergencies, but that there may be more movement among visits that did not require emergency services. Table 23 presents

[32]Note that in all regression tables, coefficients on individual diagnoses-level controls have been omitted for brevity.

the results; even broken down by severity of ED visit, there is little movement in the likelihood of admission for either Medicaid patients or Medicare/privately insured patients.

The bottom plot in Figure 8 presents the difference-in-differences plot of hospital proportion of Medicaid FFS patients over time; no clear pattern is evident. In the regression analysis presented in Table 20, the coefficient of interest is small and not statistically significant.

In all of the analyses of access to care measures, the coefficient on the explanatory variable of interest is small and non-significant. The results of these analyses together suggest that access to care may not change substantially following a change in the reimbursement methodology. This is not particularly surprising, as there is not a clear incentive for hospitals to change their admissions procedures; a switch to DRG-based payments may decrease *or* increase average payments for a given service.

4.4.3. Intensity of Care

To study the impact of the introduction of DRG payments by Medicaid on intensity of care, I study a number of measures of inpatient intensity of care. The plots in Figure 9 illustrate the trends in outcomes prior to and following DRG implementation. Table 24 presents the results of the difference-in-differences analysis of the impact of DRG implementation on inpatient length of stay. Recall that in this case, there is a clear incentive for hospitals, particularly those that were previously paid on a per diem basis, to reduce LOS. Among Medicaid patients, there is a significant reduction in length of stay (Poisson coefficient=-0.06, $p<0.01$), while there is a small but significant increase in length of stay among the Medicare and privately insured population (Poisson coefficient=0.029, $p<0.05$). Breaking down the Medicaid response by previous payment type (Table 25), both hospitals that were previously paid on a FFS basis and on a per diem basis saw reductions in LOS, but the effect is driven primarily by previous per diem hospitals. This is consistent with theoretical predictions, given that the incentive for previous per diem hospitals is completely reversed after the switch to DRG payments.

Note that for the outcomes of number of procedures and charges, previous FFS hospitals would have a strong incentive to reduce intensity, whereas previous per diem hospital would have already had that incentive. Table 26 shows the results of the analyses of the number of procedures associated with the discharge. However, the analyses show no significant changes in the number of procedures for either Medicaid patients or for Medicare/privately insured patients. When the Medicaid result is broken down by previous payment method, the result remains nonsignificant for previous per diem hospitals, but counter to theory, there is a small increase in the number of procedures in previous FFS hospitals. Table **??** presents the results on the charges associated with each discharge. Similar to the number of procedures, the size of the coefficient on $Post \times July1DRG$ for Medicaid patients is very small, and not statistically different from zero. These results hold even when broken down by previous payment type. These results together would suggest that the hospitals in this study react to the change in payments when there is a clear reversal in incentive, but do not react strongly to weaker incentives.

Table 30 presents the results of the logistic regressions on the likelihood of childbirth via cesarean section among the cohort of women admitted to the hospital for childbirth. I find a reduction in the likelihood of having a c-section by Medicaid patients following the introduction of DRG payments (OR=0.932, p<0.05). Breaking that result down by previous payment method, I find again that this response is primarily driven by hospitals that were previously paid on a per diem basis (OR=0.884, p<0.001). The effect is not significant for previous FFS hospitals, or for privately insured women. This could imply that on average, the marginal payment for a c-section relative to a vaginal birth decreased under the DRG payment system.

4.4.4. Complications of Care

To study whether the switch to DRG payments impacted the likelihood of a diagnosis being coded as having complications, I examine the likelihood of complications among women admitted to the hospital for childbirth, controlling for whether she had a c-section or a vaginal birth. Across the board for Medicaid patients (regardless of previous payment method) and for privately insured women, there were no significant effects of the switch to DRG based payments on the likelihood of having complications (Table). This implies that at least in this setting, an "upcoding" response seems unlikely, and similarly, it does not appear that changes to quality of care (if any), have strong negative impacts on patient outcomes.

4.4.5. Sensitivity Analyses

The results on the coefficient of interest from the sensitivity analyses using the county-level proportion of hospitalized patients covered by Medicaid FFS are briefly summarized in Table 34. The significant result on LOS from the main analyses is observed in the sensitivity analysis as well, and continues to be driven by hospitals previously reimbursed on a per diem basis. However, the result on the likelihood of a c-section loses statistical significance. To explore the lack of persistance in this result, I explore changes to the LOS and charges among the birth cohort, using the identification strategy from the main analysis. If the likelihood of a c-section truly increased, then there should be accompanying increases in both LOS and charges, as higher LOS and charges are associated with c-sections compared to vaginal births on average. However, I find no significant increases in LOS or charges among this population, implying that the finding of increased likelihood of c-section may be spurious.

4.4.6. Subgroup Analysis of Uninsured Population

I conducted additional analyses on the subgroup of patients who were uninsured. All patients coded with a payer type of "county indigent program," "other indigent," or "self pay" were included in this analysis. I found no significant impacts of the introductions of Medicaid DRG payments on any of the measures of access to care, intensity of care, or complications of care studied in this chapter.

4.5. Policy Implications and Discussion

4.5.1. Policy Implications

The results uncovered in this chapter show that at least along certain dimensions, hospitals are very responsive to changes in incentives. Policymakers should take into consideration that especially when the incentives change dramatically, such as the incentive for longer length of stay under a per diem payment system versus shorter length of stay under a DRG system, hospital response can be both quick and strong. While a DRG-based payment system may reduce costs to Medicaid compared to the previous systems, policy makers should also consider whether reductions in length of stay may imply lower quality of care, and how that may affect health care costs overall. Hospitals that were previously paid on a FFS basis did not have a strong response to DRG payments, contrary to theoretical predictions. Policymakers should keep in mind that responses may have occurred in the longer term than than studied in this chapter, and future work should focus on examining the long-term impact.

4.5.2. Discussion

Many state Medicaid programs, as well as the Medicare program, make use of DRG-based payments, yet existing knowledge on the impacts of this reimbursement methodology is largely based on studies of policy changes that occurred in the 1980's. Consistent with the older literature, I find significant reductions in the length of hospital stay for Medicaid patients (Ellis and McGuire, 1996; Frank and Lave, 1989; Rosko and Broyles, 1987). These reductions, however, are primarily driven by hospitals that were previously reimbursed on a per diem basis. While the same response should be expected from hospitals previously paid on a FFS basis, the result is not statistically significant (although the coefficient is in the correct direction). These findings suggest that consistent with the older literature, hospitals have a strong response along the length of stay margin to a DRG-based payment system. However, given that that response was not significant among prior FFS hospitals, it may be the case that the strength of the response depends on the prior reimbursement method, or that some hospitals may not be able to adjust in the short term.

The lack of strong response from FFS hospitals could also be explained by relatively low FFS margins. If FFS payments were relatively low, and hospitals have increasing marginal costs, they may not have been in a place where reductions to length of stay or other measures of intensity of care were feasible. Indeed, California already has a relatively short inpatient LOS on average, compared to other states, so in some hospitals there may simply have been little room to move (California HealthCare Foundation, 2010). The lack of response on other measures of intensity is perhaps unsurprising, given that for previous per diem hospitals, the incentive remained the same for measures such as the number of procedures.

Some limitations should be taken into account when considering the results of this study. First, the study is focused on a subset of hospitals within California. A problem inherent to studying Medicaid is that Medicaid programs differ from state to state, and a study of one state's program may not be nationally generalizable. However, California has one of the largest Medicaid populations in the country, serving 16% of the non-elderly population in the state, and also has a demographically diverse Medicaid population. While the study includes a large number of patients, the number of hospitals included in the control group was fairly limited, due to the way the implementation of the DRG payment system was implemented and the sample selection. However, the sensitivity analyses did not suffer from the same problem, and found the same results in terms of length of stay.

The major contribution of this research to the literature is to update the existing literature on hospital response to prospective payment. Prior to this work, existing research was largely based on policy changes in the 1980's; the healthcare landscape in the U.S. certainly looks very different today than 30 years ago.

4.6. Tables & Figures

Figure 7: Sample Selection Flowchart

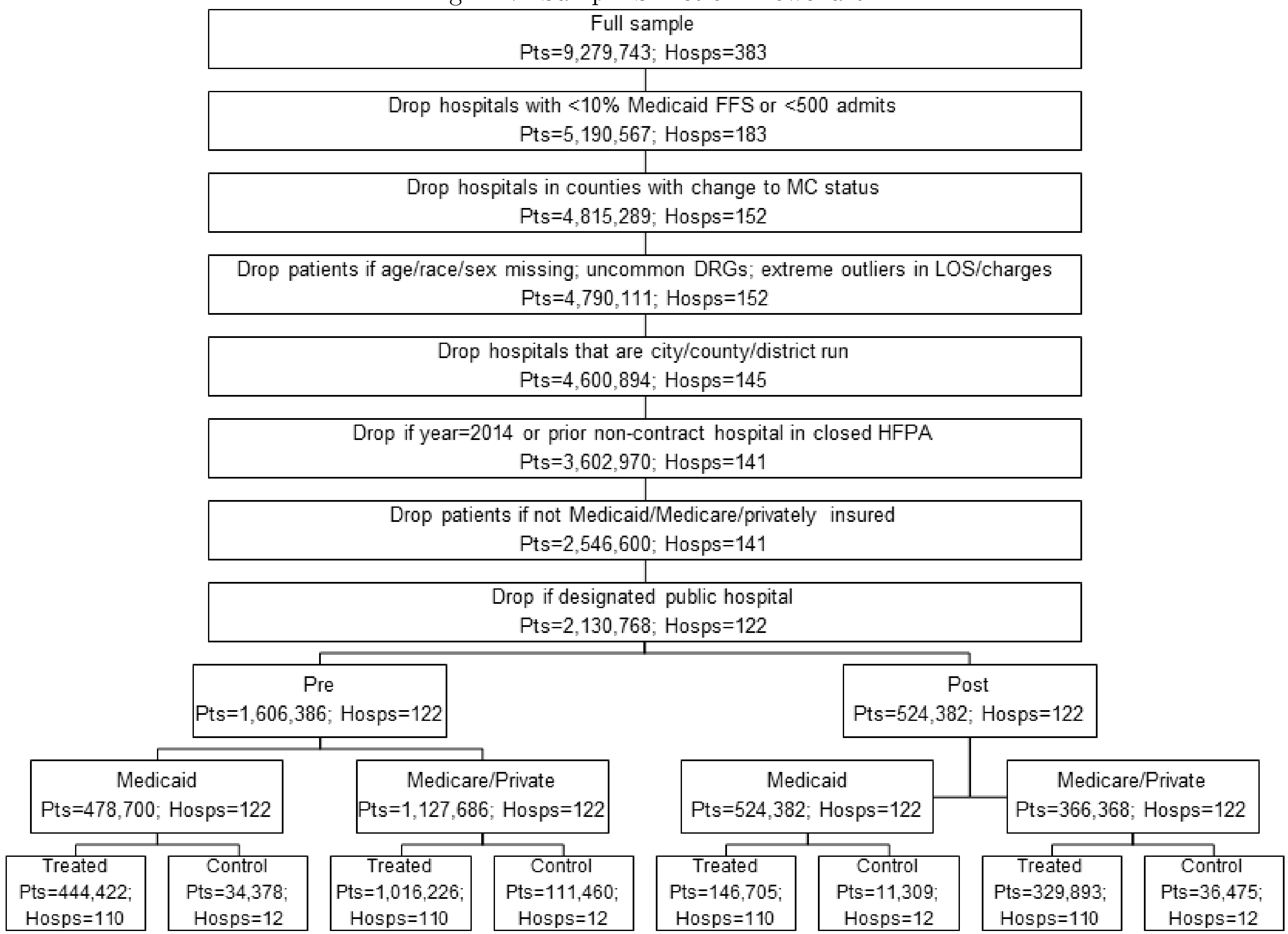


Table 18: Hospital Characteristics (2012)

	Treatment	Control
N*	110	12
Average Total Discharges	10,939	9,538
Average Medi-Cal Discharges	2,230	1,324
Average Total Hospital Days	58,842	53,990
Average Medi-Cal Days	14,853	14,108
Average Medi-Cal FFS Patient Proportion	22.6%	21.4%

Table 19: Patient Characteristics

	Medicaid				Medicare/Privately Insured			
	In Treated Hospital		In Control Hospital		In Treated Hospital		In Control Hospital	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post
N	444,422	146,705	34,278	11,309	1,016,226	329,893	111,460	36,475
Age (mean)	23.68	23.34	21.47	20.99	54.71	54.70	57.59	57.48
Gender (percentage female)	64.77	64.57	68.70	69.22	57.17	56.89	57.78	57.10
Race (percentage)								
White	60.65	59.61	63.17	60.85	69.56	69.35	79.86	78.51
Black	8.04	7.92	5.30	5.08	8.83	8.47	4.65	4.54
Native American	0.21	0.23	0.80	0.72	0.22	0.20	0.50	0.61
Asian/Pacific Islander	5.26	4.77	2.00	2.15	9.18	9.33	3.30	3.22
Other	25.13	26.66	28.03	30.55	11.55	11.96	11.31	12.69
Unknown	0.79	0.81	0.69	0.65	0.66	0.69	0.37	0.42
LOS (mean, in days)	4.21	4.67	3.71	4.38	4.44	4.64	4.43	4.57
Charges (mean)	37,629	41,488	20,749	22,885	61,657	66,667	48,263	50,911
Number of Procedures (mean)	1.49	1.53	1.25	1.21	1.64	1.70	1.54	1.54
Birth Cohort: N	116,432	39,187	11,052	3,748	83,205	27,708	10,104	3,336
Received c-section (vs. vaginal delivery) (percentage)	35.55	34.91	34.18	35.11	36.46	36.82	35.78	36.81
Delivery with complication (percentage)	16.80	16.99	19.46	19.37	18.78	19.21	17.45	16.58
ED Patients: N	2,165,481	742,756	237,534	80,874	2,436,560	780,311	291,166	100,133
Admitted to hospital (percentage)	12.03	11.52	8.49	8.00	23.56	23.24	22.76	21.56

Figure 8: Difference-in-Differences Plots: Access to Care Measures

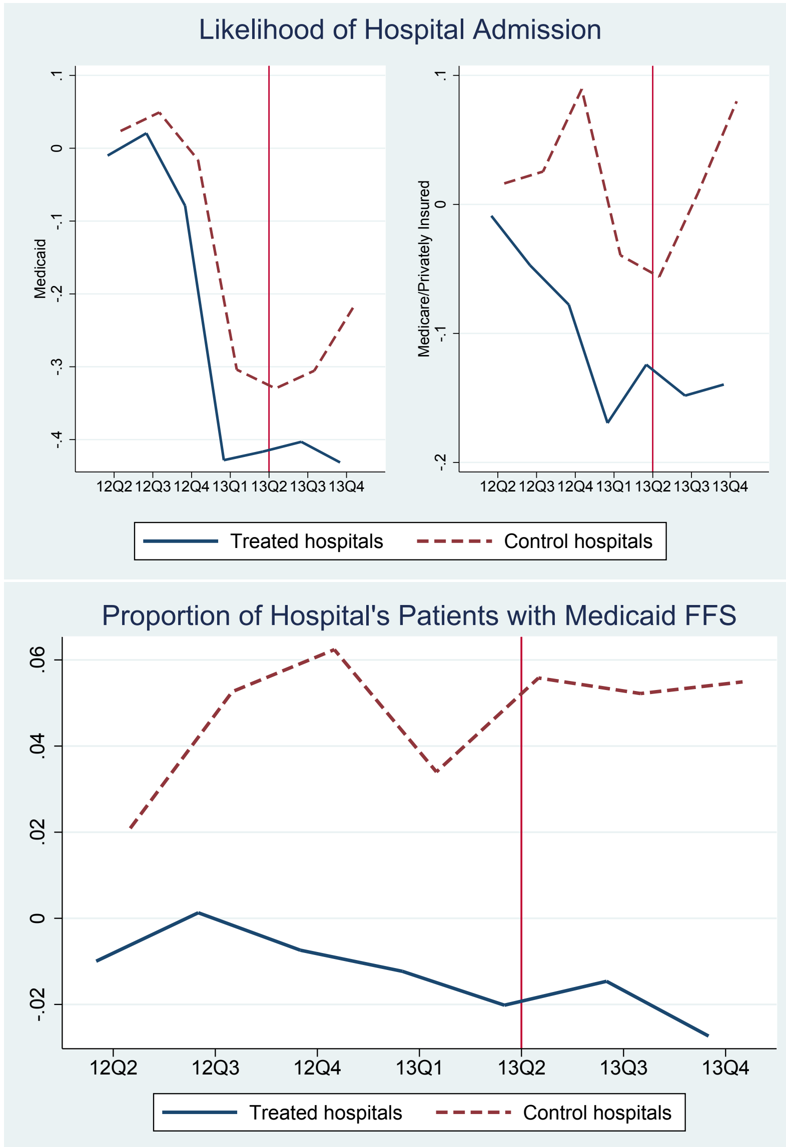


Figure 9: Difference-in-Differences Plots: Intensity of Care Measures

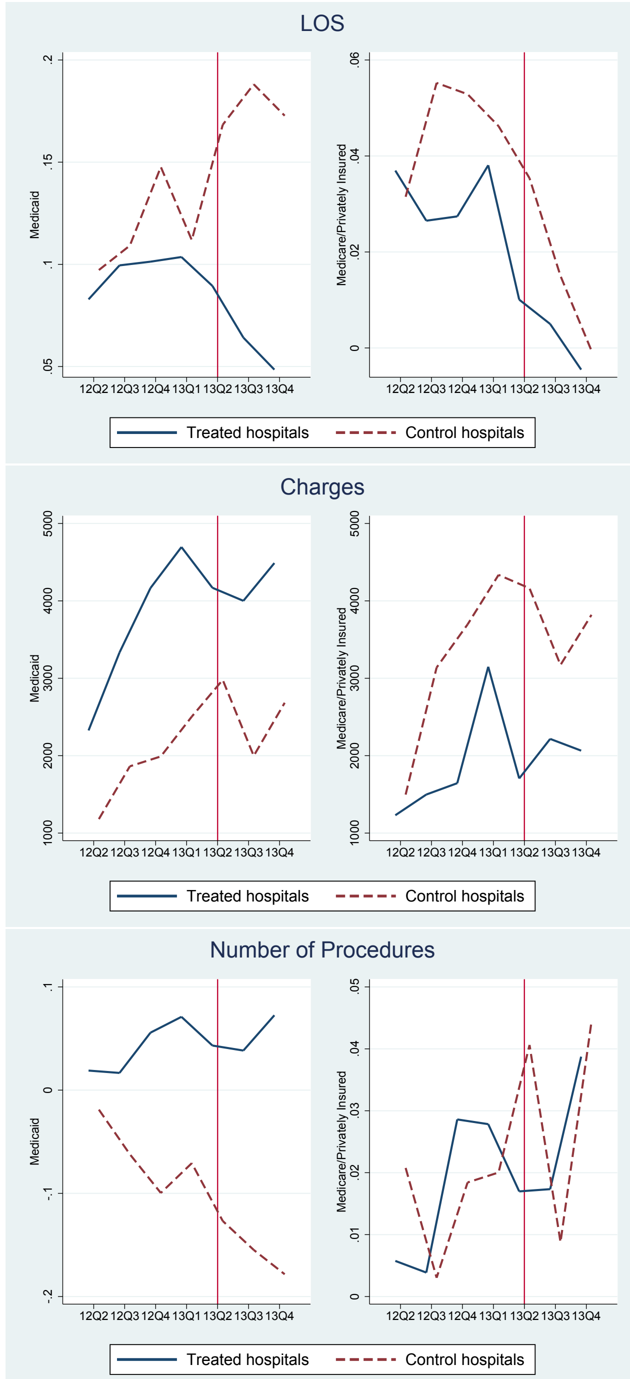


Figure 10: Difference-in-Differences Plots: Intensity of Care Measures (Birth)

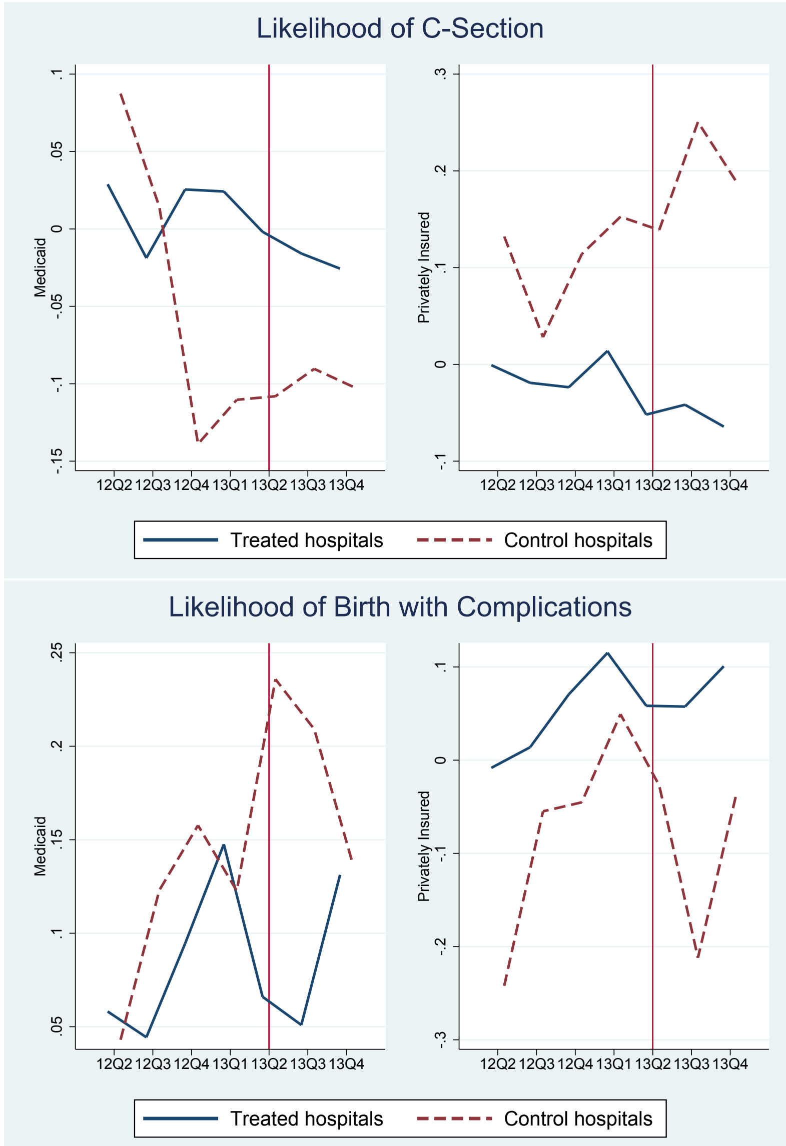


Table 20: Hospital Mix

July 1st DRG	0.118***	(0.014)
Post	-0.016	(0.018)
Post X July1DRG	0.015	(0.019)
Church	0.000	(.)
County Unemployment	0.000	(0.003)
County Average Income	0.000	(0.000)
Observations	964	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 21: Likelihood of Admission

	Medicaid		Medicare/Private	
	Odds Ratio	Std. Error	Odds Ratio	Std. Error
Admitted to Hospital				
July 1st DRG	0.451***	(0.063)	0.291***	(0.044)
Post	1.029	(0.059)	1.039	(0.051)
Post X July1DRG	0.970	(0.061)	0.964	(0.049)
Male	1.000	(.)	1.000	(.)
Female	0.741***	(0.015)	0.842***	(0.009)
White	1.000	(.)	1.000	(.)
Black	1.016	(0.059)	1.019	(0.071)
Native American/Eskimo/Aleut	0.416***	(0.078)	0.253***	(0.046)
Asian/Pacific Islander	1.333***	(0.100)	1.108*	(0.051)
Other	0.981	(0.103)	0.819**	(0.057)
Unknown	0.774	(0.352)	0.232	(0.214)
Church	1.000	(.)	1.000	(.)
County Unemployment	1.099***	(0.020)	1.050***	(0.010)
County Average Income	1.000***	(0.000)	1.000***	(0.000)
Observations	3156126		3608043	

Exponentiated coefficients; Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 22: Likelihood of Admission by Previous Payment Type

	Previous FFS		Previous Per Diem	
	Odds Ratio	Std. Error	Odds Ratio	Std. Error
Admitted to Hospital				
July 1st DRG	6.469***	(0.456)	0.421***	(0.052)
Post	0.926	(0.135)	1.079	(0.053)
Post X July1DRG	1.194	(0.201)	0.923	(0.049)
Male	1.000	(.)	1.000	(.)
Female	0.902	(0.068)	0.724***	(0.015)
White	1.000	(.)	1.000	(.)
Black	1.007	(0.085)	1.023	(0.064)
Native American/Eskimo/Aleut	0.755	(0.229)	0.317***	(0.059)
Asian/Pacific Islander	1.686	(0.470)	1.318***	(0.102)
Other	0.899	(0.434)	0.989	(0.102)
Unknown	0.179	(0.184)	1.169	(0.167)
Church	1.000	(.)	1.000	(.)
County Unemployment	1.057	(0.042)	1.109***	(0.024)
County Average Income	1.000	(0.000)	1.000***	(0.000)
Observations	421219		2732179	

Exponentiated coefficients; Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 23: Likelihood of Admission by ED Visit Severity

	ED Not Needed				ED Needed			
	Medicaid		Medicare/Private		Medicaid		Medicare/Private	
	OR	SE	OR	SE	OR	SE	OR	SE
Admitted to Hospital								
July 1st DRG	0.545***	(0.069)	0.372***	(0.063)	0.521***	(0.069)	0.375***	(0.061)
Post	0.990	(0.063)	1.001	(0.051)	1.028	(0.073)	1.028	(0.050)
Post X July1DRG	1.028	(0.070)	1.001	(0.052)	0.992	(0.074)	0.980	(0.049)
Male	1.000	(.)	1.000	(.)	1.000	(.)	1.000	(.)
Female	0.710***	(0.017)	0.827***	(0.010)	0.717***	(0.017)	0.835***	(0.010)
White	1.000	(.)	1.000	(.)	1.000	(.)	1.000	(.)
Black	1.072	(0.077)	1.022	(0.081)	1.068	(0.074)	1.044	(0.078)
Native American/Eskimo/Aleut	0.430***	(0.085)	0.238***	(0.045)	0.386***	(0.082)	0.234***	(0.042)
Asian/Pacific Islander	1.297***	(0.102)	1.059	(0.058)	1.285**	(0.108)	1.068	(0.056)
Other	0.936	(0.106)	0.777***	(0.058)	0.928	(0.103)	0.793**	(0.058)
Unknown	0.784	(0.346)	0.219	(0.197)	0.723	(0.338)	0.203	(0.184)
Church	1.000	(.)	1.000	(.)	1.000	(.)	1.000	(.)
County Unemployment	1.127***	(0.022)	1.074***	(0.013)	1.116***	(0.020)	1.060***	(0.012)
County Average Income	1.000***	(0.000)	1.000***	(0.000)	1.000***	(0.000)	1.000***	(0.000)
Observations	1944294		1921574		1726751		1897127	

Exponentiated coefficients; Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Standard errors clustered at hospital level

OR - "Odds Ratio," SE - "Standard Error"

Table 24: Length of Stay

	Medicaid		Medicare/Private	
Length of Stay				
July 1st DRG	-0.584***	(0.057)	-0.394***	(0.039)
Post	0.005	(0.020)	-0.053***	(0.014)
Post X July1DRG	-0.060**	(0.020)	0.029*	(0.015)
Male	0.000	(.)	0.000	(.)
Female	-0.023**	(0.008)	0.019***	(0.003)
White	0.000	(.)	0.000	(.)
Black	0.035*	(0.017)	0.042*	(0.020)
Native American/Eskimo/Aleut	-0.056	(0.033)	-0.048**	(0.017)
Asian/Pacific Islander	0.055*	(0.026)	0.022*	(0.010)
Other	0.003	(0.016)	0.013	(0.012)
Unknown	0.083*	(0.042)	0.024	(0.019)
Church	0.000	(.)	0.000	(.)
County Unemployment	-0.026***	(0.007)	-0.011***	(0.003)
County Average Income	0.000	(0.000)	0.000	(0.000)
Observations	597714		1485397	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 25: Length of Stay by Previous Payment Type

	Previous FFS		Previous Per Diem	
Length of Stay				
July 1st DRG	-0.284**	(0.092)	-0.566***	(0.060)
Post	-0.008	(0.036)	0.013	(0.029)
Post X July1DRG	-0.038	(0.046)	-0.069*	(0.028)
Male	0.000	(.)	0.000	(.)
Female	-0.066**	(0.021)	-0.019*	(0.008)
White	0.000	(.)	0.000	(.)
Black	0.038**	(0.014)	0.039*	(0.019)
Native American/Eskimo/Aleut	-0.068	(0.051)	-0.028	(0.038)
Asian/Pacific Islander	0.224	(0.166)	0.039	(0.023)
Other	0.036	(0.031)	0.005	(0.016)
Unknown	0.124*	(0.050)	0.084	(0.046)
Church	0.000	(.)	0.000	(.)
County Unemployment	-0.029*	(0.014)	-0.026**	(0.008)
County Average Income	0.000	(0.000)	0.000	(0.000)
Observations	55208		542506	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 26: Number of Procedures

	Medicaid		Medicare/Private	
Number of Procedures				
July 1st DRG	1.118***	(0.091)	0.566***	(0.076)
Post	-0.066	(0.041)	-0.024	(0.015)
Post X July1DRG	0.051	(0.046)	0.023	(0.018)
Male	0.000	(.)	0.000	(.)
Female	-0.021*	(0.009)	-0.032***	(0.004)
White	0.000	(.)	0.000	(.)
Black	-0.018	(0.029)	-0.014	(0.018)
Native American/Eskimo/Aleut	-0.036	(0.036)	-0.009	(0.023)
Asian/Pacific Islander	0.007	(0.022)	0.032**	(0.011)
Other	-0.010	(0.058)	0.021	(0.030)
Unknown	-0.015	(0.029)	0.006	(0.016)
Church	0.000	(.)	0.000	(.)
County Unemployment	-0.001	(0.006)	0.002	(0.004)
County Average Income	0.000	(0.000)	0.000	(0.000)
Observations	597714		1485397	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 27: Number of Procedures by Previous Payment Type

	Previous FFS		Previous Per Diem	
Number of Procedures				
July 1st DRG	-0.733***	(0.164)	1.118***	(0.092)
Post	-0.099**	(0.032)	-0.024	(0.063)
Post X July1DRG	0.111*	(0.047)	0.007	(0.068)
Male	0.000	(.)	0.000	(.)
Female	-0.042	(0.023)	-0.020*	(0.009)
White	0.000	(.)	0.000	(.)
Black	-0.028	(0.039)	-0.022	(0.030)
Native American/Eskimo/Aleut	-0.066	(0.041)	0.005	(0.035)
Asian/Pacific Islander	0.017	(0.047)	0.009	(0.023)
Other	-0.050	(0.105)	-0.011	(0.062)
Unknown	0.028	(0.101)	-0.032	(0.031)
Church	0.000	(.)	0.000	(.)
County Unemployment	0.010	(0.006)	-0.003	(0.007)
County Average Income	-0.000	(0.000)	0.000	(0.000)
Observations	55208		542506	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 28: Charges

	Medicaid		Medicare/Private	
July 1st DRG	7484**	(2454)	11530**	(3850)
Post	-831	(613)	-2226*	(871)
Post X July1DRG	-139	(602)	1881*	(905)
Male	0	(.)	0	(.)
Female	-314	(253)	-416*	(187)
White	0	(.)	0	(.)
Black	-143	(973)	-2352	(1459)
Native American/Eskimo/Aleut	-1713	(1310)	-654	(1352)
Asian/Pacific Islander	2462*	(1174)	1962	(2739)
Other	-972	(984)	-258	(1533)
Unknown	1221	(1831)	-385	(1546)
Church	0	(.)	0	(.)
County Unemployment	-1049***	(159)	-1316***	(205)
County Average Income	0*	(0)	1***	(0)
Observations	597714		1485397	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 29: Charges by Previous Payment Type

	Previous FFS		Previous Per Diem	
July 1st DRG	5714	(3810)	8107**	(2883)
Post	-959	(520)	19	(811)
Post X July1DRG	339	(720)	-1027	(779)
Male	0	(.)	0	(.)
Female	-1272	(699)	-250	(264)
White	0	(.)	0	(.)
Black	1465	(1188)	-271	(1034)
Native American/Eskimo/Aleut	-1942	(1266)	-745	(1768)
Asian/Pacific Islander	1301	(3649)	2376*	(1159)
Other	-345	(764)	-955	(1074)
Unknown	6264*	(2952)	624	(2088)
Church	0	(.)	0	(.)
County Unemployment	-407*	(184)	-1198***	(192)
County Average Income	0	(0)	0	(0)
Observations	55208		542506	

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 30: Likelihood of C-Section

	Medicaid		Privately Insured	
csection				
July 1st DRG	1.068	(0.060)	1.009	(0.053)
Post	1.006	(0.037)	1.031	(0.082)
Post X July1DRG	0.932*	(0.033)	0.976	(0.077)
White	1.000	(.)	1.000	(.)
Black	1.353***	(0.064)	1.435***	(0.070)
Native American/Eskimo/Aleut	0.883	(0.103)	0.863	(0.094)
Asian/Pacific Islander	0.764***	(0.043)	0.908*	(0.036)
Other	1.026	(0.042)	1.113**	(0.043)
Unknown	0.833	(0.090)	0.957	(0.087)
Age	1.058***	(0.002)	1.061***	(0.003)
Observations	169873		123892	

Exponentiated coefficients; Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 31: Likelihood of C-Section by Previous Payment Method

	Previous FFS		Previous Per Diem	
csection				
July 1st DRG	0.902	(0.146)	1.139	(0.093)
Post	1.002	(0.069)	1.043	(0.033)
Post X July1DRG	1.037	(0.083)	0.884***	(0.028)
White	1.000	(.)	1.000	(.)
Black	1.344**	(0.140)	1.362***	(0.069)
Native American/Eskimo/Aleut	1.118	(0.205)	0.824	(0.108)
Asian/Pacific Islander	0.842	(0.081)	0.756***	(0.044)
Other	0.892	(0.069)	1.036	(0.045)
Unknown	0.819	(0.163)	0.846	(0.099)
Age	1.057***	(0.005)	1.058***	(0.002)
Observations	16315		153558	

Exponentiated coefficients; Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 32: Likelihood of Coded 'With Complications'

	Medicaid		Privately Insured	
comp				
July 1st DRG	0.795	(0.099)	1.059	(0.108)
Post	1.022	(0.132)	0.936	(0.143)
Post X July1DRG	1.037	(0.136)	1.121	(0.175)
White	1.000	(.)	1.000	(.)
Black	1.559***	(0.103)	1.417***	(0.126)
Native American/Eskimo/Aleut	1.440**	(0.177)	1.216	(0.158)
Asian/Pacific Islander	1.015	(0.070)	0.957	(0.046)
Other	1.050	(0.082)	1.035	(0.064)
Unknown	1.052	(0.124)	1.012	(0.121)
Age	1.005**	(0.002)	1.009***	(0.002)
Observations	169873		123892	

Exponentiated coefficients; Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 33: Likelihood of Coded 'With Complications' by Previous Payment Method

	Previous FFS		Previous Per Diem	
comp				
July 1st DRG	0.731	(0.173)	0.818	(0.109)
Post	0.690	(0.207)	1.124	(0.096)
Post X July1DRG	1.488	(0.475)	0.954	(0.084)
White	1.000	(.)	1.000	(.)
Black	1.329	(0.203)	1.583***	(0.112)
Native American/Eskimo/Aleut	1.218	(0.133)	1.341	(0.251)
Asian/Pacific Islander	1.214	(0.210)	1.014	(0.073)
Other	1.050	(0.146)	1.060	(0.093)
Unknown	0.626*	(0.134)	1.100	(0.139)
Age	1.004	(0.003)	1.005*	(0.002)
Observations	16315		153558	

Exponentiated coefficients; Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Sensitivity Analysis

Table 34: Results of Sensitivity Analyses

	Coefficient on $Post \times CountyMedicaidProportion$	
	Medicaid	Medicare/Private
Likelihood of Admission from ED (OR)	0.477***	0.809
LOS (Poisson)	-0.212*	-0.086
Number of Procedures (Poisson)	-0.005	-0.032
Charges	40	-9,846
Likelihood of C-Section (OR)	2.768	0.405
Likelihood of Birth Patients Coded "With Complications" (OR)	0.662	0.758

$*p < 0.05, **p < 0.01, ***p < 0.001$

CHAPTER 5 : Conclusion

In this dissertation, I examine the impact of a level cut to Medicaid payment rates on hospital behavior, as well as the impact of a change in Medicaid reimbursement methodology on hospital behavior. Although such policy measures by state Medicaid programs have become increasingly common, current evidence is fairly limited or dated on their effects.

5.1. The Impact of Level Cuts to Medicaid Payments

I use data from the California Office of Statewide Health Planning and Development to examine the impact of a 10% cut to Medicaid FFS payment rates in the state of California. I find little evidence that the payment cut impacts access to inpatient care for Medicaid patients; I also find no evidence of changes to intensity of treatment. Given the emphasis in the existing literature on cost-shifting as a potential outcome, combined with the lack of strong or consistent empirical evidence of its occurrence, I also examine the impacts of the Medicaid price change on treatment of non-Medicaid patients. In the main analyses, I find evidence of an increased likelihood of cesarean section for privately insured women in hospitals affected by the payment cut. However, this finding did not hold up in the sensitivity and other checks, leading to the conclusion, that at best, any effect was fairly limited.

These results are not consistent with the theoretical predictions, which imply that hospitals will change the way they treat Medicaid patients, non-Medicaid patients, or both. One potential explanation for these results would be that hospitals have some altruistic reasons (which would be consistent with theory if hospitals get very high utility from quantity of care), or even legal reasons for not wanting to reduce quantity of care. It could be that hospitals instead respond to payment cuts in other, non-treatment related ways. Indeed, previous research has shown that hospitals may choose administrative, rather than treatment-related means in response to payment reductions (Dafny, 2005). The lack of effect on the non-Medicaid population is also largely consistent with the broad lack of empirical evidence for cost shifting (Frakt, 2011; Morrisey, 1996).

Policymakers should consider several implications of this research. Although Medicaid patients' treatment does not appear to be adversely affected by changes to Medicaid payments in the hospital setting, policymakers should consider whether this is truly the optimal response from Medicaid's standpoint. Policymakers may instead want to consider other, more effective measures of changing provider behavior. Policymakers should also consider other ways that hospitals may respond to payment cuts, and how these responses could affect care for Medicaid and other patients. This also highlights areas for future work. For example, hospitals may have responded to Medicaid price cuts by reducing their nursing staff, which could have implications on the quality of care provided. In addition, hospitals may have increased their use of laboratory or diagnostic testing to offset financial losses, which would certainly have lessened any cost-savings Medicaid would have otherwise seen. It may also have been the case that there was a switch from care provided in an inpatient setting to providing care in an outpatient setting in certain care settings, which could have implications for both costs and quality of care.[33] Future research should explore these other avenues of hospital response.

[33] Only inpatient payment rates were affected by the policy change.

5.2. The Impact of Changes to Medicaid Reimbursement-Based Incentives

To study the impacts of the 2013 switch to DRG-based payments by California Medicaid, I also make use of the inpatient and emergency department discharge data from the California Office of Statewide Health Planning and Development. I find no evidence that the switch to DRG payments impacted access to care for Medicaid beneficiaries. However, I do find strong evidence that hospitals reduce average inpatient length of stay in response to DRG payments, and furthermore, that this response is driven primarily by hospitals that were previously reimbursed on a per diem basis.

The results from the empirical analyses are broadly consistent with the theoretical predictions from the model in Chapter 2. Without information on the specific DRG weights and prices, changes in overall access to care cannot be predicted; indeed, I do not find any evidence of changes to access to care. While the model predicts that hospitals paid on a FFS basis will have incentive to reduce intensity of care, it is also consistent with the model that intensity remain relatively stable if FFS prices were already relatively low (which is likely, given the subject of Chapter 3 of this dissertation). Similarly, we may expect no effects on intensity of care for prior FFS hospitals if prior FFS rates were already low. For per diem hospitals, the results were also consistent with theory. These hospitals already had incentive to keep the number of procedures and amount of treatment (as measured by charges) low. However, under per diem payments, they had incentive to keep LOS high, at least in cases where the average cost per day decreased for subsequent hospital days. Once hospitals are switched to DRG payments, the incentive changes; hospitals are now incentived to keep LOS low, and I observe this effect empirically.

Policymakers should take note that hospitals remain sensitive to changes in incentive, at least along some dimensions. However, they should also consider what implications these changes in hospital behavior may have on the quality of care provided to Medicaid patients. Future work should examine the impacts on the quality of patient care with DRG payments versus other payment mechanisms. In addition, future work could delve into individual diagnoses to determine how hospitals respond based on the average change in price. Finally, it would be interesting to use a longer follow up period to understand the long term impacts of prospective payment when the data become available.

5.3. Conclusions

The difference in results between the two major empirical analyses that comprise this dissertation are interesting to note. The 2008 policy change represents a reduction in the reimbursement *level*, while the 2013 policy change represents a change in the reimbursement *methodology*. The former effected no statistically discernible changes in access or intensity of care, while the latter resulted in a reduction in length of stay consistent with theoretical predictions. Policymakers should note that the introduction of prospective payment mechanisms (where changes in incentives are clear) have consistently brought about reductions in length of stay, as observed both in this work and in the existing literature. On the other hand, changes to payment levels have brought about a variety of responses that may be context-specific, and there is no consesus in the literature on the impacts of such changes in payments. My results, together with existing literature, suggest that Medicaid policymakers should strongly consider reimbursement based incentives, where the impacts are generally consistent and predictable, rather than changes to payment levels, when contemplating various policy measures to slow the rate of cost growth associated with Medicaid.

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